



Methods and datasets for segmentation of minimally invasive surgical instruments in endoscopic images and videos: A review of the state of the art

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ABSTRACT

In the field of computer- and robot-assisted minimally invasive surgery, enormous progress has been made in recent years based on the recognition of surgical instruments in endoscopic images and videos. In particular, the determination of the position and type of instruments is of great interest. Current work involves both spatial and temporal information, with the idea that predicting the movement of surgical tools over time may improve the quality of the final segmentations. The provision of publicly available datasets has recently encouraged the development of new methods, mainly based on deep learning. In this review, we identify and characterize datasets used for method development and evaluation and quantify their frequency of use in the literature. We further present an overview of the current state of research regarding the segmentation and tracking of minimally invasive surgical instruments in endoscopic images and videos. The paper focuses on methods that work purely visually, without markers of any kind attached to the instruments, considering both single-frame semantic and instance segmentation approaches, as well as those that incorporate temporal information. The publications analyzed were identified through the platforms Google Scholar, Web of Science, and PubMed. The search terms used were “instrument segmentation”, “instrument tracking”, “surgical tool segmentation”, and “surgical tool tracking”, resulting in a total of 741 articles published between 01/2015 and 07/2023, of which 123 were included using systematic selection criteria. A discussion of the reviewed literature is provided, highlighting existing shortcomings and emphasizing the available potential for future developments.

1. Introduction

Minimally invasive surgery (MIS) offers several advantages over conventional types of surgery, making it the standard method for many surgical interventions today [1–4]. By introducing surgical instruments through narrow incisions, surgical trauma can be significantly reduced, ensuring faster patient recovery and a shortened hospital stay [1]. The movements of the surgical tools in the human body are commonly recorded using an endoscopic camera, and the images are made visible to the surgeon on a monitor. However, MIS also faces several challenges arising from the more elaborate surgical procedure, the limited field of view, and the complex hand-eye coordination. In addition, the guidance of the endoscope by a human assistant results in increased time and costs [5].

To address these challenges, the research area of computer- and robot-assisted minimally invasive surgery (RAMIS) has been experiencing increasing interest in recent years [6,7]. The development of new

techniques in this field aims to assist the surgeon in overcoming these drawbacks in the best possible way and opens up further possibilities such as surgical skill assessment, operating workflow optimization, or the training of junior surgeons. One popular approach to this is the utilization of information regarding the positions and movements of the surgical instruments over time. This can be achieved by tracking surgical tools using electromagnetic or infrared-based methods or by attaching external markers [8–11]. However, all of these techniques have in common that they require additional effort to prepare for surgery. In addition, these approaches cannot be easily integrated into the existing workflow of an operation.

For these reasons, current work focuses exclusively on purely visual-based processing of the endoscopic video stream. Due to the great success of deep-learning-based methods in the field of image processing in recent years, approaches developed in this way also represent the state of the art for this application [12–14]. Here, the detection of

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surgical instruments is often performed by object detection methods that localize the tools through comprehensive axis-aligned bounding boxes and follow them across multiple video frames using appropriate tracking methods [11,15,16]. Approaches developed using this technique often exhibit fast processing time but are usually imprecise since surgical instruments often protrude from the bottom two corners into the center of an image, resulting in maximally unfavorable conditions for the axis-aligned bounding box detection.

In contrast, segmentation methods allow a much more accurate determination of the position of surgical tools in images since the shape of the instruments can also be predicted on the basis of this pixel-by-pixel classification. Moreover, the technical advances achieved in recent years make it possible to segment surgical tools in real-time, thus providing an accurate and fast method [17–21]. In addition, these characteristics can be further improved by incorporating the temporal information inherent in video recordings through novel techniques. In addition to these technical innovations, the availability of publicly accessible datasets has also supported the increased interest in this research area. A specific contribution to this development is presented by the organization of challenges conducted as part of an annual conference organized by the Medical Image Computing and Computer Assisted Intervention Society (MICCAI)¹ [22].

In the present work, we analyze current approaches concerning semantic and instance-based segmentation of surgical instruments in endoscopic images and videos and provide possible research directions. To this end, the contributions of this work are threefold:

- Identification and characterization of robotic and non-robotic datasets used for method development and evaluation and quantification of the frequency of use in the literature.
- Systematic search and analysis of articles concerning semantic and instance-based segmentation of minimally invasive surgical instruments in endoscopic images and videos.
- Discussion of the reviewed literature, identification of existing shortcomings, and highlighting the potential for future developments.

The structure of this document is as follows. In Section 2, we describe related reviews and their considered research areas and highlight differences between the present work and these publications. Section 3 presents the conducted systematic search, describes the criteria used to select the relevant publications, and analyzes the results. The datasets employed in the relevant publications are described in more detail in Section 4, both in terms of the frequency with which the datasets were used as well as concerning their characteristic properties. A description of the selected literature regarding semantic segmentation of surgical instruments is provided in Section 5. Here, the articles are divided into single-image segmentation and segmentation involving temporal information. Instance-based methods of current literature are analyzed in Section 6, following the same structure. Subsequently, Section 7 presents articles that use the segmentation of surgical tools as a basis for further processing. The discussion of the results of the systematic search takes place in Section 8. Finally, Section 9 summarizes the results of this work, highlights the main findings, and provides an outlook on possible further developments in this research area.

2. Related work

In the following, we briefly describe the objectives of related reviews and contextualize the contributions of the present work. For this purpose, we only consider papers that exclusively address visually-based approaches without markers of any kind and that have been published since 2015. The works are arranged chronologically in ascending order.

In 2017, Bouget et al. [23] published a comprehensive review of the current state of research, identifying and analyzing commonly used datasets for the development and testing of surgical tool recognition algorithms, providing an in-depth comparison of instrument detection methods as well as highlighting existing shortcomings and providing an analysis of validation techniques to measure the quality of the approaches considered. For this purpose, the authors reviewed datasets and publications between 2000 and 2015, using the keywords “surgical tool detection”, “surgical tool tracking”, “surgical instrument detection”, and “surgical instrument tracking” on the search platforms Google Scholar and PubMed, resulting in a total of 28 articles, and considered both endoscopic and microscopic image data.

Three years later, Yang et al. [14] presented a survey with similar goals, focusing on methods based on Convolutional Neural Networks (CNNs) architectures. The authors group the considered papers based on methodological CNN-oriented approaches but do not provide specific details about the applied review method, such as the used search platforms or the number of observed publications. The search terms are composed of two necessary parts, one consisting of the terms “neural network*” or “deep learning”, and the other of “mini* invasive”, “robot* surger*”, “robot* surgical”, or “laparoscop*”, where the * operator represents an arbitrary continuation of the respective expression.

In 2021, the work of Anteby et al. [12] was published, which, in addition to determining the presence and localization of surgical tools, considers many other tasks, such as surgical phase detection, classification and segmentation of anatomy, determination of surgical actions, or even prediction of the required surgical time. A total of 32 identified papers were considered relevant after searching the platforms Medline, Embase, IEEE Xplore, and Web of Science for publications between January 2012 and May 2020.

In the same year, Rivas-Blanco et al. [13] provided a review on deep-learning-based methods in minimally invasive surgery that covers the area of surgical image analysis, surgical task analysis, surgical skill assessment, and automation of surgical skills. The keywords for the search on the IEEE Xplorer, Springer Link, Science Direct, and ACM Digital Library platforms consisted of two parts, the first of which had to contain the terms “deep learning” or “deep neural network” and the second of which had to contain “laparoscopic surgery”, “minimally invasive surgery”, “robotic surgery”, or “robot-assisted surgery”. A total of 85 papers between 2015 and 2020 were considered.

In 2022, Nema and Vachhani [24] investigated current trends in artificial intelligence (AI)-based visual detection and tracking of surgical instruments and its application to surgical skill assessment. The authors do not specify details regarding the applied review methodology, such as databases considered, search terms, or time period.

A more comprehensive analysis and summary of current research regarding visual detection and tracking of minimally invasive surgical instruments was presented in 2022 by Wang et al. [11], who analyze the literature concerning various aspects. The approaches were identified by searching the platforms Web of Science, Google Scholar, PubMed, and CNKI using the search terms “object detection”, “object tracking”, “surgical tool detection”, “surgical tool tracking”, “surgical instrument detection”, and “surgical instrument tracking”, including articles published between 1985 and 2021.

Looking at these reviews, it is noticeable that the focus is often on tasks such as binary tool presence detection, surgical action determination, surgical phase recognition, or surgical skill assessment, with object detection methods using axis-oriented bounding boxes being the central approach while segmentation of minimally invasive instruments tends to play a minor role. This observation is due to the fact that none of the search terms used in the aforementioned works contains the keyword “segmentation”, whereas the term “detection” is frequently used. Due to the rapid increase in the number of publications in this area in recent years, which is illustrated in Fig. 1 and described in more detail in Section 3, some of the results of the above reviews no longer

¹ <http://www.miccai.org/>

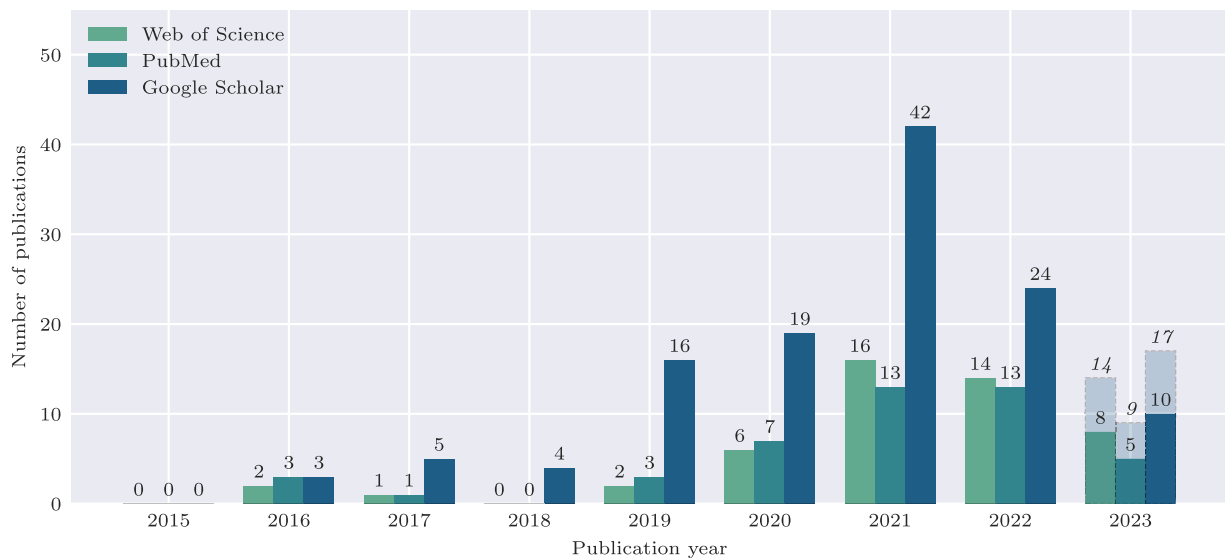


Fig. 1. Number of relevant publications by year resulting from searches on the platforms Web of Science, PubMed, and Google Scholar, according to the selection criteria. For 2023, in addition to the publications up to and including July, the numbers of expected papers by the end of the year are shown in italics at the top of the transparent boxes.

represent the current state of the art, both in terms of freely available datasets as well as regarding published methods. Another limitation of the presented works is that the search methods used often lack central details, such as the time period considered, the search platforms used, keywords, inclusion and exclusion criteria, or the number and type of articles identified, which reduces the traceability and informative value of the results.

The focus of this paper is explicitly to provide an overview of the current state of research concerning methods and datasets for the semantic and instance-based segmentation and tracking of minimally invasive surgical instruments in endoscopic images and videos. To this end, we specify our approach in detail concerning the search methodology, including the search platforms, the search terms, the time period, the information extracted from the articles, and the selection criteria used, followed by an analysis of the results. In order to demonstrate the transferability and applicability of segmentation methods to clinical applications, we also present publications that use surgical instrument segmentation as a basis for further processing in robotic-assisted settings. We present a discussion and in-depth analysis of the literature reviewed, related to the datasets currently being used to develop and validate new approaches and related to the methodologies identified, emphasizing existing shortcomings and highlighting the available potential for future developments.

3. Review methodology

The publications for this work were identified by systematic search on the platforms Google Scholar, Web of Science, and PubMed. The search terms used were “instrument segmentation”, “instrument tracking”, “surgical tool segmentation”, and “surgical tool tracking”, and all articles published between 01/2015 and 07/2023 were included. For all platforms, the search was based on the titles of the publications. An article was retrieved if all parts appeared for one of these search terms. For each publication, we identified the title, the datasets used, and the type of segmentation, i.e., whether it is semantic or instance segmentation, as well as whether it concerns binary, instrument type, or instrument part segmentation. Furthermore, for each article, it was reviewed whether temporal information was used to track surgical instruments or to improve segmentation quality, and if so, what methodology was used to do so. Only publications written in the English language and which have undergone a peer-review process were considered, resulting in the exclusion of 5 and 26 articles,

respectively. In the following, the criteria that a publication must fulfill to be included as a relevant paper in this review are presented first. Subsequently, the results of the systematic search are analyzed.

3.1. Selection criteria

We considered only publications with methods developed and validated on the basis of endoscopic imaging data, excluding all articles employing data of a different nature. A publication meets the criterion if the developed method has been validated with at least one endoscopic data set. Furthermore, we concentrate on new methodological developments and not on the pure application of methods in the field of semantic and instance-based segmentation of minimally invasive surgical instruments. Articles concerning other research areas as object recognition or pose estimation are excluded from the results. The processing of the endoscopic image data must be exclusively visual, which means that we excluded methods utilizing external markers of all possible types on the instruments from the results. Publications that do not present new methodological developments regarding the segmentation of surgical tools, but which utilize the results of the segmentation as a foundation for further actions, were included in the present work and described separately from the novel methodological developments.

3.2. Analysis of the results

The search on the Google Scholar platform retrieved 423 results, the search on Web of Science returned 208 matches, and the search on PubMed resulted in 110 articles. According to the selection criteria, 123 (29.1%), 49 (23.6%), and 45 (40.9%) results were relevant for Google Scholar, Web of Science, and PubMed, respectively. A representation of the relevant publications for the respective years is shown in Fig. 1. It can be seen that Google Scholar has the highest number of publications meeting the selection criteria in each year. Furthermore, all included articles are already covered by Google Scholar, resulting in 123 publications taking all three search platforms into account. A positive trend can be noticed across all search platforms until 2021, indicating a strong increase in research in this area in recent years. Since this review only covers the first seven months of 2023, the expected number of publications by the end of the year is given on the top of the transparent boxes, assuming a linear increase in the number of papers.

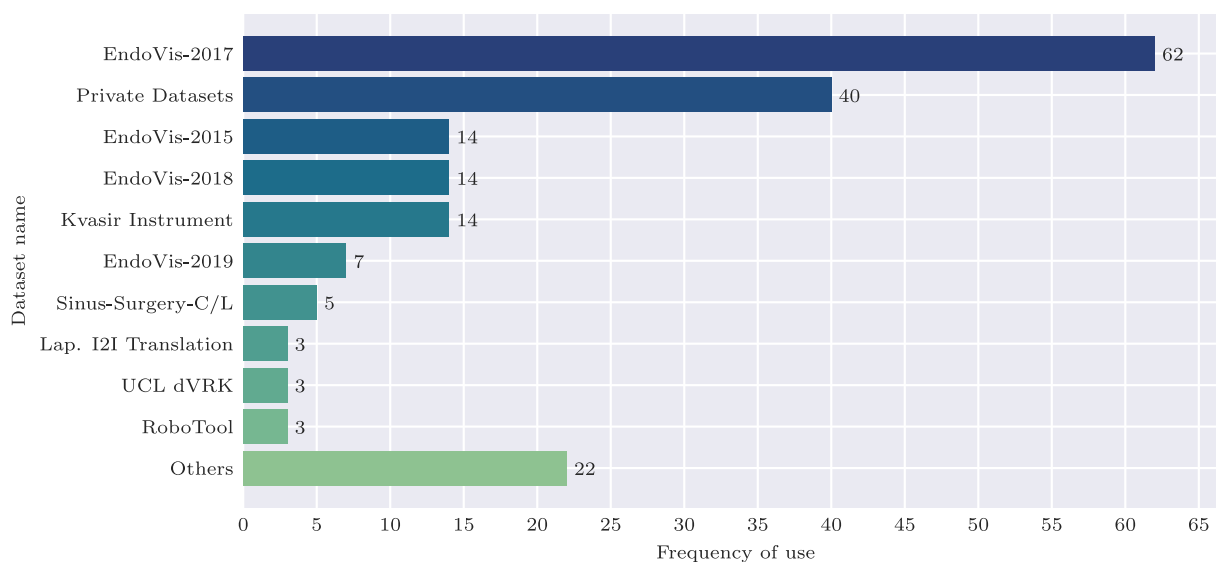


Fig. 2. Visualization of commonly used datasets along with their frequency of use in recent publications.

4. Public datasets

The provision of freely available datasets had a central impact on the development of new methods concerning segmentation and tracking of surgical instruments in endoscopic images and videos in recent years [22]. In the following, we present publicly available datasets for surgical instrument segmentation. For this purpose, we first consider the datasets that are commonly used in recent work and in the publications included in this review, according to the selection criteria. To provide a comprehensive overview of all available datasets, we further characterize datasets that are not used in the publications of this review but provide segmentations of surgical instruments and are available for the development of new methods.

Fig. 2 shows a visualization regarding the frequency of use of the datasets employed in the considered papers. A total of 187 datasets were used in the 123 publications considered, divided into nine relevant datasets, private non-public datasets, and datasets that did not meet the criteria for relevant datasets. The criteria for a dataset to be considered relevant are that surgical instruments are present, that segmentation ground truths are available for these instruments, and that they consist of endoscopic images or videos. All datasets that are not publicly available are grouped under the term “Private Datasets”. The term “Others” includes all datasets that are publicly available but do not meet the relevant criteria described above. It can be seen that the EndoVis-2017 dataset [25] was used in a total of 62 publications, making it by far the most frequently used dataset. This is followed by the group of private datasets used in a total of 40 publications. Ranked third, fourth, fifth, and sixth most frequently used datasets are the EndoVis-2015 [26], EndoVis-2018 [27], Kvasir Instrument [28], and EndoVis-2019 [29] datasets, with 14, 14, 14, and seven utilizations, respectively. The Sinus Surgery-C/L dataset [30,31] was referenced seven times. Three times each, the results of publications were based on the datasets labeled Laparoscopic Image-to-Image Translation [32], UCL dVRK [33], and RoboTool [34]. Furthermore, 22 publications utilized datasets that did not correspond to any of the above groups.

An overview of the datasets together with their corresponding references and website links can be seen in Table 1. The upper part of the table contains datasets that have been used in the literature of this review and meet the above mentioned criteria. The lower part describes datasets that also contain segmentations of surgical instruments, but either do not meet all of these criteria or were not used by any relevant publication in the time period considered. Datasets are sorted in ascending order by the year of their publication.

Various characteristics of the datasets are given in Table 2. For each dataset, the type of instruments, the resolution of the video images, the type of procedure shown, whether the images are in-vivo or ex-vivo along with the type of tissue, and the size of the dataset consisting of the number of frames annotated and the number of sequences are listed. Unfortunately, no information is available if the datasets are retrospective or prospective in nature. For the relevant datasets, which belong to the upper part of the table and are listed in Fig. 2, an example image for each dataset is shown in Fig. 3.

In the following, these nine relevant datasets with their characteristics are described in more detail, followed by the properties of the seven additional freely available datasets. As in Tables 1, 2, and Fig. 2, the datasets are each sorted in ascending order by the time of their publication.

4.1. EndoVis 2015 - Instrument Segmentation and Tracking

As part of the MICCAI 2015 conference, the Instrument Segmentation and Tracking sub-challenge was organized and conducted which can be divided into the two tasks of segmenting surgical instruments in single endoscopic images and tracking them over time in endoscopic image sequences. The dataset includes in-vivo images of laparoscopic colorectal procedures using rigid instruments and frames from ex-vivo environments using robotic tools.

For rigid instrument segmentation, 160 annotated images are available for training, extracted from four sequences in equal numbers. Ten additional images from each sequence and 50 frames from each of the two additional sequences are provided for validation purposes. The tracking training dataset with rigid instruments consists of four sequences of 45 seconds each, of which one image per second is annotated. For validation, one frame per second is provided for a further 15 seconds per sequence and two additional recordings of one minute each. All in-vivo images have a resolution of 640×480 . For segmentation, each pixel is assigned to one of the classes background, shaft, and manipulator, while for tracking the surgical tool, the coordinates of the center of the shaft end and the orientation of the instrument are also available.

For the segmentation of robotic instruments in ex-vivo images, four sequences of 45 seconds each are available for training, with each video frame annotated. A further 15 seconds of recording from each of the four sequences and two one-minute videos are available for validation, with each frame annotated. The video data of the tracking dataset regarding robotic instruments is identical to that of the segmentation,

Table 1

Publicly available endoscopic datasets together with their corresponding references (Ref.) and website links. The upper part contains datasets used in surveyed literature, while the lower part lists other freely available data that are available for the development of segmentation methods. The datasets are each sorted in ascending order by year of publication.

Dataset	Ref.	Website
EndoVis 2015	[26]	https://endovissub-instrument.grand-challenge.org
EndoVis 2017	[25]	https://endovissub2017-roboticinstrumentsegmentation.grand-challenge.org
EndoVis 2018	[27]	https://endovissub2018-roboticscenesegmentation.grand-challenge.org
EndoVis 2019	[29]	https://robustmis2019.grand-challenge.org/
Lap. I2I Translation	[32]	http://opencas.dkfz.de/image2image
Sinus-Surgery-C/L	[30,31]	http://hdl.handle.net/1773/45396
UCL dVRK	[33]	https://www.ucl.ac.uk/interventional-surgical-sciences/weiss-open-research/weiss-open-data-server/ex-vivo-dvrk-segmentation-dataset-kinematic-data
Kvasir Instrument	[28]	https://datasets.simula.no/kvasir-instrument
RoboTool	[34]	https://www.synapse.org/#!Synapse:syn22427422
InstrumentCrowd	[35]	https://opencas.webarchiv.kit.edu/?q=InstrumentCrowd
NeuroSurgicalTools	[36]	https://medicis.univ-rennes1.fr/software
CholecSeg8k	[37]	https://www.kaggle.com/datasets/news1ab/cholecseg8k
HeiSurF	[38]	https://www.synapse.org/#!Synapse:syn25101790/wiki/608802
ART-Net	[39]	https://github.com/kamruleee51/ART-Net
CaDIS	[40]	https://cataracts-semantic-segmentation2020.grand-challenge.org
AutoLaparo	[41]	https://autolaparo.github.io

except that the annotations differ. All ex-vivo images have a resolution of 720×576 . For segmentation, each pixel is assigned to one of the classes background, shaft, head, and clasper, while for surgical tool tracking, posture information in the form of rotation, translation, and articulation of the instrument head and claspers is provided.

4.2. EndoVis 2017 - Robotic Instrument Segmentation

Two years after the first MICCAI sub-challenge focused on the segmentation of surgical tools in endoscopic images, the Robotic Instrument Segmentation sub-challenge was conducted in 2017 with a similar objective. The data provided for this sub-challenge deals with abdominal porcine procedures performed exclusively with robotic instruments and recorded by a da Vinci Xi system. Eight video sequences are available for training, each with 225 annotated frames, with one image annotated per second. An additional 75 video frames for each sequence and two additional sequences of 300 images each are provided for validation. All video frames have a resolution of 1920×1080 and represent in-vivo recordings. The segmentation distinguishes between the instruments large needle driver, prograsp forceps, monopolar curved scissors, cadriere forceps, bipolar forceps, vessel sealer, and a drop-in ultrasound probe. Furthermore, each instrument is divided into three parts.

4.3. EndoVis 2018 - Robotic Scene Segmentation

As part of the MICCAI 2018 conference, the Robotic Scene Segmentation dataset was released, with video sequences showing porcine surgical procedures. The dataset consists of 19 video sequences, 15 for training and four for validation. As with the EndoVis 2017 dataset, only robotic instruments are visible over porcine tissue, and the recordings were captured using the da Vinci X and da Vinci Xi System. The videos have a resolution of 1280×1024 and were taken with a stereo endoscope. In addition to the instrument classes and their subdivisions of the different instrument parts used in the Robotic Instrument Segmentation sub-challenge of 2017, suturing needles, suturing thread, suction-irrigation devices, and surgical clips were segmented. In addition to these non-biological categories, the kidney parenchyma, the kidney fascia, and perinephric fat, which the authors called “covered kidney” and small intestine were also annotated.

4.4. EndoVis 2019 - Robust Medical Instrument Segmentation

The Robust Medical Instrument Segmentation (ROBUST-MIS) dataset was published in 2019. The aim was to investigate the robustness and

generalization ability of different algorithms developed within the sub-challenge and to identify particular challenges in the images. For this purpose, the authors provided a total of 30 surgical procedures, representing in equal parts rectal resection procedures, proctocolectomy procedures, and sigmoid resection procedures, containing 10,040 annotated images. The recordings feature real-life in-vivo human surgeries performed with rigid instruments. The videos were recorded in high definition (HD) quality, downsampled and provided to challenge participants at a resolution of 960×540 . The performance of the developed procedures in terms of generalization ability and quality is investigated in three stages, with increasing complexity. In stage one, test data was taken from the procedures (patients) from which the training data were extracted. In stage two, test data was obtained from the same type of surgery as the training data but from procedures (patients) not included in the training. Finally, in stage three, test data originates from a different but similar type of surgery (and different patients) compared to the training data. The instruments are assigned an instance class with incremental numbering, which means that as soon as a new instrument appears in an image, it is labeled a number one higher than the previous highest category. As examples of instrument categories, the authors name grasper, scalpel, (transparent) trocar, clip applicator, hooks, stapling device, and suction.

4.5. Laparoscopic Image-to-Image (I2I) Translation

The Laparoscopic Image-to-Image (I2I) Translation dataset contains 20,000 automatically annotated synthetic images generated by 3D laparoscopic simulations created from the CT scans of ten patients. The images include a rendered view of laparoscopic scenes captured under random camera positioning. The authors trained a translation network and subsequently translated all rendered images with five randomly drawn style vectors for each image, resulting in a total of 100,000 images. Furthermore, all images were translated with five styles from the Cholec80 [42] dataset, which also shows images from in-vivo laparoscopic videos, resulting in another dataset of 100,000 images as well, representing the visual features of the Cholec80 dataset. All images are provided at a resolution of 452×256 . Included in the laparoscopic images are the two conventional surgical instruments grasper and hook, with the shafts and tips of the two instruments annotated as one instrument subclass each.

4.6. Sinus-Surgery-C/L

The Sinus-Surgery-C/L dataset consists of two subsets, the Sinus-Surgery-C dataset, which shows surgical procedures on cadaver specimens, and the Sinus-Surgery-L dataset, which contains real procedures

Table 2

Properties of publicly available datasets. Indicated are the type of instruments, the resolution of the video images, the kind of procedure shown, whether the frames are in-vivo or ex-vivo recordings along with the type of tissue, and the size of the dataset consisting of the number of annotated images and the number of sequences. The upper part contains datasets used in surveyed literature, while the lower part lists other freely available data that are available for the development of segmentation methods. The datasets are each sorted in ascending order by year of publication.

Dataset	Instruments		Resolution	Procedure	Data type		Size	
	Rigid	Robotic			Ex-vivo	In-vivo	# Images	# Seq.
EndoVis 2015 - Seg.	✓		640 × 480	laparoscopy		human	300	6
EndoVis 2015 - Track.	✓		640 × 480	laparoscopy		human	360	6
EndoVis 2015 - Seg.		✓	720 × 576		porcine		9,000	6
EndoVis 2015 - Track.		✓	720 × 576		porcine		9,000	6
EndoVis 2017		✓	1920 × 1080	abdominal		porcine	3,000	10
EndoVis 2018		✓	1280 × 1024	nephrectomy		porcine	2,831	19
EndoVis 2019	✓		960 × 540	laparoscopy		human	10,040	30
Lap. I2I Translation	✓		452 × 256	laparoscopy		human	20,000	–
Sinus-Surgery-C/L	✓		240 × 240	sinus surgery		human	9,003	13
UCL dVRK		✓	538 × 701	animal tissue	various animals		4,200	20
Kvasir Instrument	✓		[720 × 576, 1280 × 1024]	gastroscopy & colonoscopy		human	590	–
RoboTool		✓	varying	varying		human	514	20
InstrumentCrowd	✓		640 × 480	laparoscopy		human	120	6
NeuroSurgicalTools	✓		612 × 460	neurosurgery		human	2,476	14
CholecSeg8k	✓		854 × 480	laparoscopy		human	8,080	17
HeiSurF	✓		[720 × 576, 1920 × 1080]	laparoscopy		human	829	33
ART-Net	✓		1920 × 1080	laparoscopy		human	635	29
CaDIS	✓		960 × 540	cataract surgery		human	4,670	25
AutoLaparo	✓		1920 × 1080	laparoscopy		human	1,800	21

performed on living humans. For the Sinus-Surgery-C dataset, ten surgical procedures were recorded from five different cadaver specimens, ranging in duration from five to 23 min. The videos were recorded at a framerate of 30 FPS and a resolution of 320 × 240, and one frame was annotated every two seconds. The authors provide 4345 annotated images cropped to a size of 240 × 240, of which 3606 contain instruments. The Sinus Surgery-L dataset includes only three surgical procedures on three different patients, with a total duration of 2.5 hours. The recording and creation of the annotations followed the same procedure as for the Sinus-Surgery-C dataset. A total of 4658 annotated video frames are provided, of which 4344 contain instruments. The dataset creators note that the Sinus-Surgery-L dataset is more complicated than the Sinus-Surgery-C dataset due to challenges such as multiple instrument types, sometimes insufficient visualization, and body excretions that can alter the scene. In both datasets, the same micro-debrider instrument was used, and the segmentation masks contain information for each pixel whether it belongs to the instrument used or to the background.

4.7. UCL dVRK

The dataset entitled “Ex-vivo dVRK (da Vinci Research Kit) segmentation dataset with kinematic data” provides both segmentation masks and kinematic data for 14 surgical procedures with 300 video frames each. The authors first perform movements with surgical instruments recorded by the dVRK system. These movements are then placed over tissues from different types of animals and over a green screen. The segmentation masks of the instruments are then determined by subtracting the greenscreen background. The authors freely provide all the data used to generate the dataset, including the kinematic data of the motions of the instruments, the motion images over the greenscreen background, and the final movements of the tools over tissues along with the associated segmentation masks. For the development of own methodologies with the help of the dataset, the first eight sequences should be used for training, the two following recordings for validation, and videos 11–14 for testing. The images were captured at an original resolution of 720 × 576 and cropped to 701 × 538. The only instrument in the recordings is the EndoWrist Large Needle Driver, which may appear more than once in an image. The segmentation masks contain the information for each pixel, whether it belongs to an instrument or the background, which means that a binary segmentation is performed.

4.8. Kvasir Instrument

The dataset “Kvasir-Instrument: Diagnostic and Therapeutic Tool Segmentation Dataset in Gastrointestinal Endoscopy” was released in 2019 and provides annotations for 590 endoscopic frames acquired in gastroscopies and colonoscopies. The images include diagnostic and therapeutic tools and have different resolutions between 720 × 576 and 1280 × 1024. The authors provide both binary segmentation masks and bounding boxes. Examples of GI instruments in the dataset include snares, balloons, and biopsy forceps. Examples of GI instruments in the dataset include snares, balloons, and biopsy forceps.

4.9. RoboTool

For the creation of the RoboTool dataset, 514 video frames were manually annotated from 20 publicly available surgical procedures. The recordings show exclusively robotic instruments, and the resolution of the video frames is based on the respective source video recordings. There exist only binary labels indicating whether a given pixel belongs to an instrument or the background. In addition, the authors provide images that can be used to create a synthetic dataset. This consists of 14,720 foreground images showing between one and three surgical robotic instruments (of a total of 17 different types) in front of a green screen, of which 13,613 images have a resolution of 4032 × 3024 and the remaining 3360 × 2240. For each foreground image, the binary segmentation mask of the instruments is provided. Furthermore, 6130 background images with different resolutions showing human tissue from 50 publicly available surgical frames in which no instruments are present are provided. The authors also supply the source code for blending the foreground images onto the background ones.

4.10. Further datasets

In addition to these regularly used datasets identified in the recent literature, several others are available for the development of novel segmentation methods, which are listed along with their respective characteristics in the lower part of Table 2.

In their work from 2014, Maier-Hein et al. [35] investigate whether the annotation quality of a large number of anonymized non-experts is

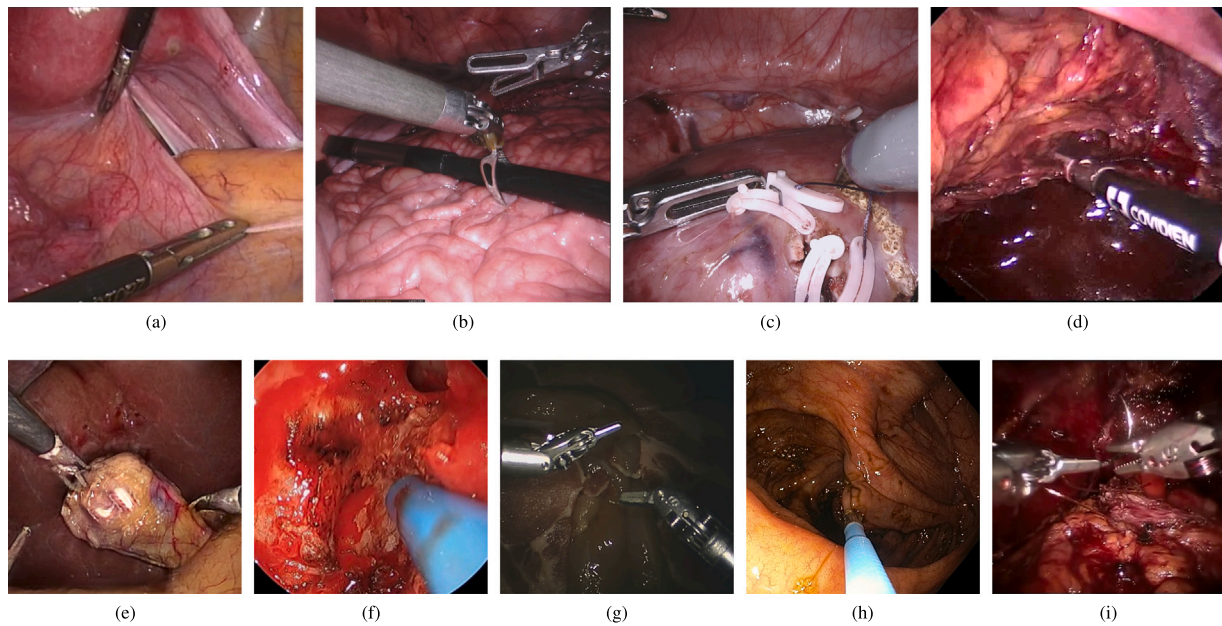


Fig. 3. Example images from frequently used endoscopic datasets, according to the upper part of Table 2. Images are taken from the EndoVis-2015 (a), EndoVis-2017 (b), EndoVis-2018 (c), EndoVis-2019 (d), Lap. I2I Translation (e), Sinus-Surgery-C/L (f), UCL dVRK (g), Kvasir Instrument (h), and RoboTool (i) datasets.

comparable to that of medical experts. For this purpose, the authors created and published a dataset consisting of six surgical procedures with a resolution of 640×480 , three each of laparoscopic adrenalectomies and laparoscopic pancreatic resections. Twenty frames were extracted from each procedure, ten of which were annotated by medical experts. Ten non-expert annotations are available for all 120 available images. A separate segmentation mask exists for each instrument within an image, resulting in a total of 2350 segmented instruments.

The NeuroSurgicalTools dataset [36] contains 2476 annotated images with binary segmentations of surgical instruments during tumor removal. Fourteen sequences were acquired with a neurosurgical microscope and the resolution of all videos was scaled to 612×460 . Instruments in the dataset included suction tubes, bipolar forceps, retractors, hooks, scalpels, pliers, and scissors, resulting in 3819 segmented individual tools.

To use the Cholec80 dataset [42] also for segmentation tasks, Hong et al. published the CholecSeg8k dataset [37] in 2020. The authors extracted and labeled 8080 laparoscopic cholecystectomy images from 17 video recordings with a resolution of 854×480 . Thirteen classes were divided, two of which were laparoscopic instruments, namely the L-hook electrocautery and grasping forceps.

As part of the MICCAI 2021 conference, the “HeiChole Surgical Workflow Analysis and Full Scene Segmentation (HeiSurF)” challenge [38] was conducted and the dataset used for it was published. The represented surgeries are laparoscopic gallbladder resections. The focus is on full scene segmentation and surgical workflow analysis, for which the actions performed and the current phase of an operation is annotated in addition to the ground truth of the segmentation. The training data consists of two parts. In the first part, images are annotated at two-minute intervals from 24 procedures, while the second part consists of short sequences of each video annotated at 1 FPS. The test data consists of nine unpublished surgeries. The resolution of the recordings varies from 720×576 to 1920×1080 . In addition to the categories for tissues and organs, there is a global instrument class, a class for drains, clips, one for trocars, and a class for specimen bags.

The “Augmented Reality Tool Network (ART-Net)” dataset [39] consists of 29 procedures representing laparoscopic hysterectomies performed with non-robotic instruments. In addition to binary segmentation of surgical instruments, tool presence, and instrument-specific

geometric primitives are also annotated. All recordings correspond to a resolution of 1920×1080 .

The “Cataract Dataset for Image Segmentation (CaDIS)” [40] is a collection of 25 video recordings and 4670 annotated frames showing cataract surgery that was used in a MICCAI challenge in 2020. Three tasks are described for which annotations are provided with different granularity, i.e., different instruments and tissue types are distinguished in more detail. There are 29 different instrument classes, 4 anatomy classes, and 3 categories for different objects appearing in the scene. All images have been scaled to a resolution of 960×540 .

The AutoLaparo dataset [41] provides sub-datasets for the tasks workflow recognition, laparoscope motion prediction, and instrument and key anatomy segmentation. A total of 21 videos of laparoscopic hysterectomies are provided, recorded at a resolution of 1920×1080 . In addition to the anatomy-based segmentation of the uterus, four types of instruments are distinguished in the recordings, namely grasping forceps, ligasure, dissecting and grasping forceps, and electric hook.

The freely available datasets described are limited by the fact that only those were selected that contain annotations for surgical instrument segmentation. For a detailed overview of datasets available for other tasks in the surgical context, such as action classification, phase recognition, surgical skill assessment, or segmentation of anatomical structures, we refer to the works of Maier-Hein et al. [7] and Rodrigues et al. [22].

5. Semantic segmentation methods

The following presents current semantic segmentation approaches, divided into two chapters and several subchapters, as shown in Fig. 4. First, contributions to the segmentation of single images are described, followed by approaches that address the segmentation of images incorporating temporal information from successive video frames.

5.1. Single frame segmentation

This section deals exclusively with publications focusing on the semantic segmentation of single images, for which 72 contributions were identified. In the following these are characterized and logically grouped according to different characteristics. First, the type of segmentation is examined, i.e., work on binary, instrument type-based, and

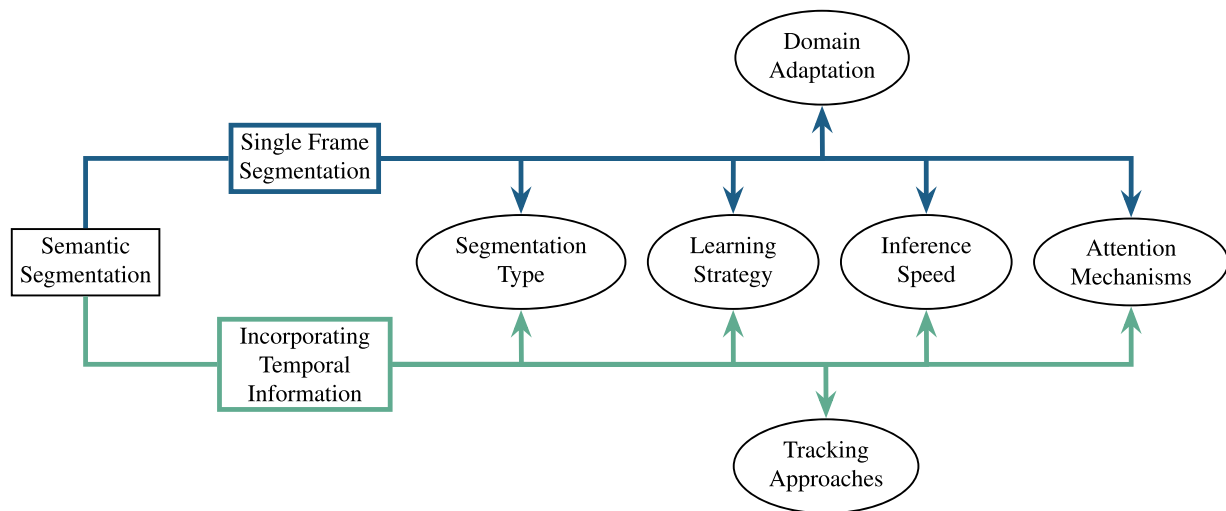


Fig. 4. Structure of Section 5 regarding semantic segmentation methods, to be read from left to right. Indicated are the topics by which the identified publications are grouped. The methods of both single-frame segmentation (Section 5.1) and those involving temporal information (Section 5.2) are divided by segmentation type (Sections 5.1.1 and 5.2.1), learning strategy (Sections 5.1.2 and 5.2.2), inference speed (Sections 5.1.4 and 5.2.4), and attention mechanisms (Sections 5.1.5 and 5.2.5). For single-frame segmentation, methods of domain adaptation 5.1.3 are further presented, and for publications with temporal information tracking approaches (Section 5.2.3) are explained.

instrument part-based segmentation is reviewed. Each of these three types has different requirements and challenges, and the segmentation of instrument parts is usually more complex than the segmentation of pure instruments, which in turn is more difficult to evaluate than the binary distinction between instruments and background. The developments are then organized according to the following learning strategies: supervised learning, semi-supervised learning, weakly-supervised learning, and work that does not fit into any of these categories. We further provide methods that focus on the adaptation to new domains. Following this, we present contributions that focus on developing real-time or near-real-time approaches and explicitly state the processing speed of their methods for this purpose. Finally, we give an overview of recent developments incorporating attention-based techniques into network architectures and highlight how this methodology improves segmentation quality.

5.1.1. Segmentation type

The number of relevant publications per segmentation type is visualized in Fig. 5, where only those segmentation types and combinations are listed that are used in at least one paper. Table 3 shows all works dealing with binary segmentation of instruments, which corresponds to the largest group. Approaches focusing on other segmentation types are presented in Table 4, subdivided according to the categories shown in Fig. 5. For each article the supervision strategy, a binary indicator of whether attention mechanisms were employed in the methodology, and the datasets used are provided. Methods developed using a supervised approach are labeled SV, unsupervised developed methods are

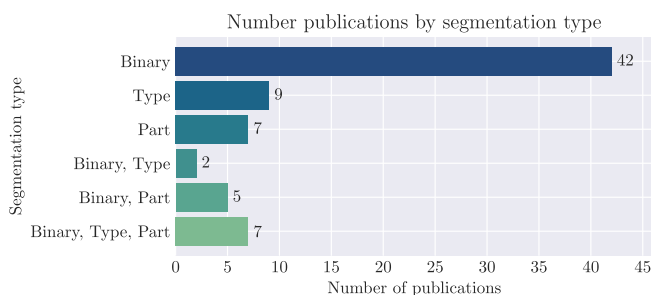


Fig. 5. Number of relevant publications per segmentation type for semantic single image segmentation.

marked USV, weakly supervised approaches are identified as WE, semi-supervised methods using SE, methods dealing with the generation and/or use of synthetic data are indicated as SN and methods dealing with the task of domain adaptation are labeled DA. When specifying the datasets used, the meaning of the columns “Private” and “Other” is identical to the one described in Section 4. If a publication uses several datasets that are not publicly available and thus belong to the “Private” category or uses several datasets that were not recorded endoscopically or not contain surgical instruments and thus belong to the “Other” category, the corresponding column is marked only once.

5.1.2. Learning strategies

The following is a review of the works identified concerning the learning strategies used. For this purpose, they are divided into supervised, semi-supervised, weakly supervised, and other types of learning methods. An overview of the number of papers according to each learning method is presented in Fig. 6.

Supervised learning

Supervised learning methods represent a group of approaches in which neural networks are trained using pixel-precise segmentation masks, which serve as the ground truth. Most of the reviewed work regarding single-image segmentation of surgical instruments in endoscopic images and videos has been developed using this approach. Here, most of the work focuses on improving the segmentation quality by developing new architectures or adapting existing architectures by enhancing certain components [30,39,43–68].

Other developments aim at improving segmentation quality by adding parallel processing of an auxiliary task. In addition to predicting the segmentation, this can include information about whether an instrument is present in a video frame or not, as well as the determination of geometric primitives [39]. Other work estimates a saliency map in addition to segmentation and computes a scan path from it [18]. Improvements in segmentation quality can be achieved by predicting bounding box coordinates in parallel [69] or by estimating a localization heatmap [53]. Recent research also shows that additional depth estimation in stereo images leads to better segmentation results [57,70]. Regarding instrument shape, current developments show that additional auxiliary contour supervision leads to more precise contour shape predictions for final segmentation [30]. Another supervised method relies on tool-pose-informed variable center morphological polar transform, by which segmentation in endoscopic images is improved [71].

In contrast to the above works, current research also deals with the comparison regarding the strengths and weaknesses of existing supervised methods on specific validation datasets [20,72,73].

However, following a supervised learning strategy and, thus, needing annotated data to develop novel methods faces several challenges, as labeling the data is a time-consuming and costly process that is typically performed manually.

Semi-supervised learning

Semi-supervised learning is one approach to address the challenges posed by the need for annotated data. This requires a sufficiently large amount of data, of which only a small fraction needs to be annotated, thus significantly reducing the annotation effort. Developments in this area are based on teacher-student learning approaches, which are well-established methods for this purpose and have been used successfully in other domains of semi-supervised learning. Recent work proposes an approach that learns on annotated synthetic and unlabeled real-world data, combining loss functions from both branches [74]. A different approach by Sanchez-Matilla et al. [75] describes a method based on semi-supervised learning and weak supervision. The authors propose an adaptive loss that allows training the network when only a small amount of annotated data is available. A semi-supervised contrastive learning approach published by Lou et al. [76] adapts the idea of solving a min-max similarity problem by classifying and projecting all-negative and positive-negative feature pairs, which are used to optimize the minimum-maximum similarity problem.

Weakly-supervised learning

To overcome the lack of annotated data, the field of self-supervised learning, often referred to as weakly supervised learning, is an active area of research. These approaches either require no annotation at all or only very simple and rapidly generated manual annotations. Two types of weakly supervised learning can be distinguished.

One method is to automatically generate labels based on image data and then use this generated target data to train a neural network. An approach to creating the training labels is to use the estimate of a robot's kinematic model in terms of the shape of the surgical tool to learn a projection of this data onto the input image using a cost function based on the GrabCut algorithm. This target data is then employed to train a segmentation network [77]. In the work of Pakhomov et al. [85], the authors also propose a process where imprecise kinematic data is used to generate training labels, and mappings between surgical images and automatically generated masks are performed using an unpaired GAN-based I2I translation approach. The training of a segmentation network is then performed using the weak target data generated in this way. Another method is to obtain labels using both electromagnetic tracking and laparoscopic image processing and then use these labels to train a lightweight network [82]. Another work uses existing models

trained on publicly available datasets to semi-automatically generate the training dataset and processes the results using a watershed-based segmentation method. A two-step training process is then used where the input images are first processed using the publicly available segmentation model, and the results are refined using a GrabCut-based algorithm [83]. A similar approach by Huang et al. [17] generates ground truth segmentation masks through a model trained on a publicly available dataset and uses these masks to train their network for joint segmentation prediction and disparity estimation.

A second way to apply weakly supervised learning is to work only with manually generated coarse annotations that can be acquired quickly and cost-effectively. By providing bounding boxes as weak annotations, training datasets for segmentation tasks can be generated by applying the DeepMAC [94] method. Subsequently, segmentation models are trained using these target data and domain-adapted synthetically generated data [84]. An efficient method for creating a training dataset is described by Papp et al. [86], where only one video frame per second is manually labeled, and all intervening video frames are semi-automatically annotated by applying optical flow (OF)-based tracking. Four established segmentation networks were trained with the annotations generated in this way, to assess the surgical skills of the operators. The creation of weak labels can also be aided by the use of a virtual reality (VR) simulator, where the ground truth is determined from this data with minimal manual effort, rendering the instruments with a solid white color and the background with uniform black color at three different levels of realism. The data generated in this way can then be used to train segmentation networks [80]. An alternative approach to semi-automatically generate the training dataset is to create coarse, scribble-like weak annotations of the tools and transform them into training data using a graph-based method. Subsequently, a segmentation model is trained using these noisy annotations in a two-step process divided into a warm-up phase and a stabilization phase, characterized by the use of highly noisy weak annotations in the warm-up phase and less noisy labels in the stabilization phase [92].

Different learning approaches

This section deals with approaches that do not fit strictly into the previously mentioned learning variants. In their work, Qin et al. [87] describe a segmentation network that is trained in a two-step procedure. In the first step, the feature extractor is trained unsupervised on a large set of unlabeled data. In the second step, they train the segmentation part of the network in a supervised fashion on a small set of annotated images. The CNN results are fused with the kinematic pose of the instruments to obtain the final predictions. The application of a GAN-based unpaired I2I approach to surgical instrument segmentation is presented by Zhang et al. [93]. The core concepts are an embedded constraint, which specifies that each pixel belongs to either an instrument or background, and the use of textured instrument images as annotations for the network generator rather than segmentation masks. The approach of Nema and Vachhani [102] also relies on a CycleGAN architecture that learns a mapping between raw surgical images and segmentation maps for instruments in an unsupervised manner, with the objective of using sparsely available training data to achieve optimal results for a large amount of unseen test data. In contrast to previously presented methods, the approach described by Su et al. [90] is based on classical image processing methods and does not include machine learning elements. The authors present a multi-stage approach that is essentially based on the fusion of shape matching using a discrete Fourier transform and a color mask determined by log-likelihood. The same authors describe a similar method, which relies on the same elements and deals with the segmentation of surgical tools and their 3D reconstruction [89].

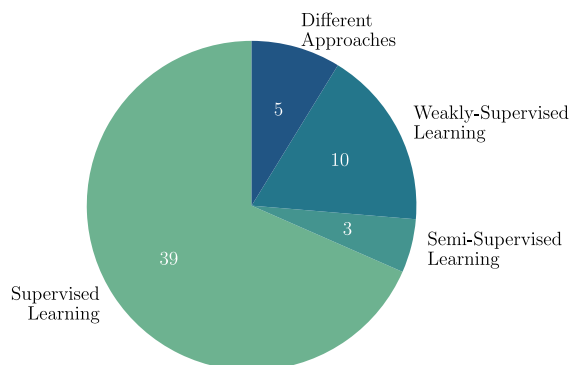


Fig. 6. Amount of relevant papers for single image semantic segmentation divided according to the respective learning strategies used.

Table 3

Publications that contributed in the area of binary semantic single-image segmentation of surgical instruments. For each publication, the type of methodology (SV = supervised, USV = unsupervised, WE = weakly-supervised, SE = semi-supervised, SN = synthetic data, DA = domain adaptation), whether or not attention mechanisms (Att.) were used in the methodology, and the datasets used are indicated.

Publication	Supervision	Att.	Used datasets												
			EndoVis				Lap. I2I	Sinus Surg.	UCL dVRK	Kvasir Inst.	Robo-Tool	Private	Other		
			15	17	18	19									
Banik et al. (2021) [43]	SV										✓				
Chou (2021) [44]	SV	✓									✓				
da Costa Rocha et al. (2019) [77]	WE													✓	
Devi et al. (2022) [45]	SV										✓				
Galdran (2021) [47]	SV										✓				
Garcia-P.-H. et al. (2017) [78]	SV		✓												
Garcia-P.-H. et al. (2021) [79]	SN			✓									✓		
Hasan et al. (2021) [39]	SV			✓										✓	
Hasan et al. (2021) [49]	SV		✓												
Heredia Perez et al. (2020) [80]	SN													✓	
Huang et al. (2022) [17]	WE													✓	
Huang et al. (2022) [71]	SV								✓					✓	
Jha et al. (2021) [20]	SV	✓					✓								
Kalavakonda et al. (2019) [73]	SV			✓											✓
Kalia et al. (2021) [81]	DA			✓						✓					
Keprate and Pandey (2021) [52]	SV										✓				
Lee et al. (2019) [82]	WE													✓	
Lee et al. (2019) [83]	WE			✓											
Leifman et al. (2022) [84]	WE, SN, DA			✓			✓						✓		
Lou et al. (2023) [76]	SE			✓							✓			✓	
Ni et al. (2019) [54]	SV	✓		✓										✓	
Pakhomov et al. (2020) [85]	WE			✓											
Papp et al. (2022) [86]	WE			✓				✓							
Psychogyios et al. (2022) [70]	SV, DA			✓											✓
Qin et al. (2019) [87]	USV, SV			✓										✓	
Qin et al. (2020) [30]	SV			✓					✓						
Rajak and Mirza (2021) [55]	SV										✓				
Sahu et al. (2020) [88]	SN, DA		✓					✓						✓	
Sahu et al. (2021) [74]	SE, SN, DA		✓				✓	✓						✓	
Su et al. (2018) [89]	USV													✓	
Su et al. (2018) [90]	USV													✓	
Suzuki et al. (2019) [57]	SV			✓											
Wang et al. (2021) [60]	SV		✓												✓
Wang et al. (2022) [91]	SN, DA			✓	✓										
Yang et al. (2022) [62]	SV	✓		✓							✓				
Yang et al. (2022) [63]	SV	✓		✓							✓				
Yang et al. (2022) [92]	WE			✓											
Yang et al. (2023) [64]	SV	✓		✓							✓				
Yang et al. (2023) [65]	SV	✓		✓					✓						
Yeung (2021) [66]	SV	✓		✓							✓				
Yu et al. (2020) [67]	SV			✓											
Zhang et al. (2021) [93]	USV			✓										✓	

5.1.3. Domain adaptation

Another frequent requirement is the adaptation to changes in the domain, e.g., concerning new instrument sets or different types of operations. In these cases, retraining for the adapted circumstances would be needed. One approach that meets this challenge is called domain adaptation. Often, such approaches employ a two-step process in which synthetic data is generated first and then used in the training process, which is also referred to as simulation-supervised learning [105].

A commonly used way to do this is to use unpaired I2I translation to translate data from a synthetic to a given real-world domain, i.e., to generate artificial images that look as realistic as possible on the desired target domain. For this purpose, architectures based on generative adversarial networks (GANs), specifically CycleGAN architectures [110], are frequently used. The resulting artificial images are then employed to train a neural network [84,103,105,111]. However, domain adaptation based on the generation of synthetic data can also be performed in other ways. One possibility is to use a VR simulator to generate endoscopic data with different levels of realism, train a segmentation network with this data, and evaluate the influence of the degree of realism of the simulated data on the predictive quality of the network [80]. A further possibility for the generation of artificial training data is the blending of images. In a promising approach, Wang et al. [91] select an image from the EndoVis-2018 dataset that shows

only background and does not contain any tools, and multiply it by applying a variety of augmentations. Then, images containing instruments are selected for the foreground, these instruments are extracted, and the background is made transparent. The instruments are then blended onto the background images, and the resulting dataset is used to train a segmentation network whose performance is also evaluated on a different real-world dataset.

In addition, there is work in the field of domain adaptation that does not use a two-step process not uses I2I-based techniques. Instead, a model based on consistency is trained simultaneously for real-world and simulated data in an end-to-end manner. In this approach, the simulated data are processed according to a supervised technique, whereas the images of the real-world domain are processed according to a consistency learning strategy, combining the losses of both branches [88]. An improvement of this method is described by Sahu et al. [74] by improving the generation of the pseudo-labels for data belonging to the real-world domain.

Another type of domain adaptation deals with the transfer from an annotated dataset to an unknown one for which no labels are available and which represents a divergent surgical scene. Here, both datasets show real-world interventions, and unlike the methods described above, this formulation of the problem does not involve artificially generated data been in advance. Regardless of the domain shift

Table 4

Publications that contributed in the area of non-binary semantic single-image segmentation of surgical instruments. For each publication, the type of methodology (SV = supervised, USV = unsupervised, WE = weakly-supervised, SE = semi-supervised, SN = synthetic data, DA = domain adaptation), whether or not attention mechanisms (Att.) were used in the methodology, and the datasets used are indicated. The works are grouped according to the segmentation types visualized in Fig. 5, excluding the binary category.

Publication	Super-vision	Att.	Used Datasets									
			EndoVis			Lap. I2I	Sinus Surg.	UCL dVRK	Kvasir Inst.	Robo-Tool	Pri-vate	Ot-her
			15	17	18							
Liu et al. (2021) [95]	DA			✓	✓							
Ni et al. (2020) [96]	SV	✓		✓								✓
Ni et al. (2020) [97]	SV	✓		✓								✓
Ni et al. (2021) [98]	SV	✓		✓								✓
Ni et al. (2022) [99]	SV	✓		✓								✓
Sanchez-Matilla et al. (2021) [75]	SE				✓							
Shen et al. (2023) [56]	SV	✓		✓	✓					✓		
Wang et al. (2023) [61]	SV	✓		✓	✓							✓
Xue and Gu (2021) [100]	SV	✓								✓		
Andersen et al. (2021) [101]	SV										✓	
Dong et al. (2021) [46]	SV			✓				✓				
Guo et al. (2022) [48]	SV		✓	✓	✓							
He et al. (2020) [50]	SV	✓	✓	✓	✓							
Nema and Vachhani (2023) [102]	SV, USV		✓									
Ozawa et al. (2021) [103]	SN, DA										✓	
Sun et al. (2021) [104]	SV			✓								
Islam et al. (2019) [18]	SV	✓		✓								
Islam et al. (2020) [69]	SV	✓		✓								
Colleoni et al. (2022) [105]	SN, DA	✓		✓				✓				✓
Laina et al. (2017) [53]	SV		✓									✓
Mahmood et al. (2022) [106]	SV			✓				✓				
Pakhomov et al. (2019) [107]	SV			✓								
Pakhomov and Navab (2020) [21]	SV			✓								
Islam et al. (2019) [19]	SV			✓								
Kamrul H. and Linte (2019) [51]	SV			✓								
Liu et al. (2022) [108]	DA			✓	✓							
Shvets et al. (2018) [109]	SV			✓								
Vishal and Kumar (2018) [58]	SV	✓		✓								
Wang et al. (2021) [59]	SV	✓		✓								✓
Zhou et al. (2021) [68]	SV	✓		✓								

considered, unpaired I2I translation based on CycleGAN architectures is also used for this purpose. Kalia et al. [81] present an approach in which the generator performs the transfer from the labeled to the unlabeled dataset, learns a segmentation model based on these results, and influences the generator in the process. Other approaches use graph-based neural networks to best model the relationships between the two domains. This involves extracting relevant features of the input images of both domains through a CNN and processing them through different regions with associated responsibilities in the graph-based network [95,108].

A further type of domain adaptation is described in the work of Psychogyios et al. [70]. The authors present an architecture that jointly estimates the disparity and segmentation of surgical tools. The segmentation task is performed in a supervised manner using annotations available only for the left image of the stereo camera, and the disparity estimation is modeled as an auxiliary task, improving the performance in terms of disparity estimation only by training the segmentation task.

In addition to work aimed at improving quality in various aspects through domain adaptation, some publications focus on the creation and provision of synthetic datasets. One way is by moving and recording instruments against a uniform background, automatically segmenting the tools, and blending them into images showing only the background [79].

5.1.4. Inference speed

Besides improving the quality of segmentation, recent work focuses on fast processing and preferably real-time processing capability of the proposed applications, which represents a prerequisite to be applicable in real-world scenarios. In this context, the speed at inference time represents an important criterion. In the literature, this speed is often specified in frames per second (FPS), i.e., the number of video frames

a method processes within one second. In our review, we obtained a total of 19 contributions presented in Table 5 that determined and reported the inference speed of their methods concerning the semantic segmentation of individual frames. To allow for a fair comparison, these works are listed together with their respective processing speed at inference time in FPS, image resolution, used GPU and the number of graphics cards used, and CPU and the amount of CPUs used.

5.1.5. Attention mechanisms

In addition to the established network architectures and components used for segmentation tasks, current research explores the potential of attention techniques. These address the limitations associated with traditional CNN-based approaches. The core idea is to use attention-based mechanisms to extract more useful features and to better suppress irrelevant ones resulting in improved segmentation quality.

Current work in the field of single-frame segmentation of surgical instruments shows promising results that achieved by using attention-oriented methods, in particular by modifying and extending parts of encoder-decoder-based architectures. Other work uses attention-based mechanisms for a dual-model filtering strategy to reduce the number of false-positive predicted pixels [44]. In unpaired I2I translation with CycleGAN-based architectures, generated synthetic images can be improved by integrating an attention module trained in parallel with the generator, supporting the model to focus on domain-specific features [105]. Approaches that address the problem of overparameterization of neural networks demonstrate the benefit of dynamic attention-based pruning strategies that identify and eliminate non-meaningful features after each encoder block [69]. Other recent research examines the impact of differently designed attention-based modules deployed in the skip connections, i.e., the links between the encoder and decoder

Table 5

Semantic segmentation methods for single images that have specified processing speeds at inference time. Indicated are the publication, the speed in FPS, the image resolution, the GPU used as well as the number of graphics cards, and the CPU used and the number of CPUs. The publications are sorted in descending order according to the reported inference speed.

Publication	Inf. speed (FPS)	Resolution	GPU	# GPU	CPU	# CPU
Islam et al. (2019) [19]	174	1024 × 1280	GTX 1080 Ti	1	–	–
Huang et al. (2022) [17]	172	192 × 384	RTX 2080 Ti	1	–	–
Guo et al. (2022) [48]	171, 175	1024 × 1280	GTX 1070	1	2.80 GHz	1
Islam et al. (2019) [18]	127	–	GTX 1080 Ti	3	–	–
Pakhomov and Navab (2020) [21]	125	1024 × 1280	Tesla P100	1	–	–
Jha et al. (2021) [20]	102	540 × 960	DGX-2	1	–	–
Shen et al. (2023) [56]	102	512 × 640	RTX A6000	1	Xeon Gold 6226R	1
Andersen et al. (2021) [101]	90	448 × 448	RTX 2080 Ti	1	–	–
	36	672 × 1120				
Garcia-P.-H. et al. (2021) [78]	43/29/8	576 × 720	GTX Titan X	1	Xeon E5-1650 3.50 GHz	1
Lou et al. (2023) [76]	40	288 × 512	RTX A5000	1	–	–
Ni et al. (2020) [96]	39	544 × 960	Titan X	1	–	–
Sun et al. (2021) [104]	37	1024 × 1280	P6000	1	–	–
Xue and Gu (2021) [100]	25	224 × 224	–	–	–	–
Psychogyios et al. (2022) [70]	22	1024 × 1280	DGX V100	1	–	–
Sanchez-Matilla et al. (2021) [75]	22	512 × 512	RTX 6000	1	–	–
Mahmood et al. (2022) [106]	21	512 × 512	GTX 1070	1	Core-i7-7700 3.60 GHz	1
		512 × 640				
Islam et al. (2020) [69]	18	1024 × 1280	RTX 2080 Ti	1	–	–
Shvets et al. (2018) [109]	11/6/5	1024 × 1280	GTX 1080 Ti	1	–	–
Su et al. (2018) [90]	6	480 × 640	No GPU	0	–	–

blocks [58,59,66]. In addition to this work the use of attention-based techniques with a particular focus on the decoder part of architectures is being investigated, for example, by adding such an attention module after each decoder block [54]. Related recent research describes how the use of attention-based techniques in a second, parallel decoder branch with a divergent task has a positive effect on segmentation quality. Of all the models compared by Jha et al. [20], the model with the best results uses an autoencoder combined with attention modules as an additional branch in the decoder to refine the features of the encoder part, and Islam et al. [18] include attention-based modules into a parallel decoder branch to predict a saliency map. Also focusing on the decoder, Shen et al. [56] integrate a block attention fusion module into the decoder for efficient feature localization and global context understanding. Between the lightweight encoder and the decoder, a branch balance aggregation module is placed, which is responsible for the fusion of feature maps of different levels as well as for the suppression of noise in the low-level feature maps. Yang et al. [62] use attention-based techniques both in the bottleneck layer in the encoder part of the network to better capture global concepts of the input, as well as in the form of a dual-attention module that combines the high-level features and the low-level features of the decoder and encoder, respectively. Therein, valuable features are recognized and irrelevant ones are suppressed, thus improving the overall segmentation quality. To overcome the drawbacks of convolutional neural networks concerning the capture of features of smaller objects as well as weaknesses in the processing of local semantic features, Yang et al. [64] introduce a multi-scale attention fusion network, which relies on an attention fusion module that integrates multi-scale information by cross-scale feature fusion. Capturing multi-scale information and using attention-based fusion modules is also the central objective of the method of Yang et al. [63,65], who aim to suppress irrelevant information in the low-level features by using attention feature fusion modules and additive attention and concatenation modules in their proposed network architecture. By using guidance connection attention modules, Wang et al. [61] also attempt to eliminate irrelevant low-level features. In addition, the inclusion of local information and local-global dependencies through bidirectional attention modules to identify accurate instrument features is also a central aspect of their method.

5.2. Incorporating temporal information

This section presents recent research on semantic surgical instrument segmentation incorporating temporal information. In the following, these works are analyzed according to the type of segmentation, the learning strategies, the methodological approaches used to segment and track the tools over time, the inference speed, and the incorporation of attention-based techniques to improve the segmentation results.

5.2.1. Segmentation type

The division of segmentation types for the papers considered in this chapter is visualized in Fig. 7, and a listing showing all publications grouped by these types is presented in Table 6, whose structure is identical to the one described in Section 5.1.

5.2.2. Learning strategies

Regarding the learning strategies, the included literature can be divided into various groups presented together with their appearance in Fig. 8. The majority of the reviewed methods are based on supervised approaches [114,116,117,126,127]. To overcome the lack of annotated data, some works present semi-supervised methods using sparsely labeled video sequences [124,128,129]. Jin et al. [128] present a module through which the network's prediction for an unlabeled frame is applied to the previous annotated frame, and a loss is computed using its ground truth. In the contribution of Zhao et al. [129], motion flows



Fig. 7. Number of relevant publications per segmentation type for semantic image segmentation incorporating temporal information.

Table 6

Publications that have contributed in the area of semantic segmentation of surgical instruments by incorporating temporal information. For each publication, the type of methodology (SV = supervised, USV = unsupervised, WE = weakly-supervised, SE = semi-supervised, SN = synthetic data, DA = domain adaptation), whether or not attention mechanisms (Att.) were used in the methodology, and the datasets used are indicated. The works are grouped according to the used segmentation types visualized in Fig. 7.

Publication	Super- vision	Att.	Used Datasets										
			EndoVis				Lap. I2I	Sinus Surg.	UCL dVRK	Kvasir Inst.	Robo- Tool	Pri- vate	Ot- her
			15	17	18	19							
Agustinos and Voros (2015) [112]	USV											✓	
Amini Khoiy et al. (2016) [113]	USV											✓	
Attia et al. (2017) [114]	SV	✓											
Du et al. (2016) [115]	SV, USV	✓										✓	
Garcia-P.-H. et al. (2016) [116]	SV, USV	✓									✓	✓	
Lin et al. (2019) [117]	SV										✓		
Lin et al. (2021) [118]	SV	✓				✓							
Liu et al. (2020) [119]	WE		✓										
Sestini et al. (2023) [120]	USV		✓						✓			✓	
Yang et al. (2022) [121]	SV	✓					✓						
Zhao et al. (2021) [122]	DA	✓	✓	✓							✓	✓	
Zhao et al. (2021) [123]	DA		✓	✓							✓		
Li et al. (2021) [124]	SE, USV		✓										
Zhang and Gao (2020) [125]	SV										✓		
Islam et al. (2021) [126]	SV	✓	✓										
Wang et al. (2021) [127]	SV	✓	✓	✓									
Jin et al. (2019) [128]	SE, USV	✓	✓										
Zhao et al. (2020) [129]	SE, USV		✓										

are learned in two parallel branches to propagating the annotations available for a few locations to the unlabeled video frames. Then, the manually created annotations, the propagated annotations, and the labels for additional interpolated frames are used to train a segmentation network. Based on this approach, the work of Li et al. [124] presents a method for improving the interpolation of the images and the associated labels between the annotated frames. Various approaches use elements of unsupervised learning in addition to the above learning strategies to track the instruments over time, which are described in a later topic within this section [116,120,124,128,129].

A different approach is taken by Liu et al. [119], which operates in a weakly supervised manner. Instead of annotated data, automatically generated pseudo-labels based on the input images and manually specified cues are used. These pseudo-labels then serve as ground truth and are used to compute an anchor loss. As with single-image segmentation, there exists research in the area of domain adaptation based on the incorporation of temporal information. Zhao et al. [122, 123] present related approaches in which initial models are learned through meta-learning and then applied to new domains through an online adaptation scheme, requiring only an annotation for the first frame of a video sequence at inference time. An unsupervised three-stage approach that consists solely of implicit motion information and instrument-oriented shape-priors is provided by Sestini et al. [120]. Working entirely without manual annotations or prior knowledge is the approach of Agustinos and Voros [112], where the 3D pose of the instruments is determined in a multi-step procedure using classical image processing techniques, essentially based on the use of the Frangi filter. The method from Amini Khoiy et al. [113] also works only with color features, first converting the input image to the more informative hue, saturation, value (HSV) color space, then performing V+S histogram thresholding followed by the application of a filter on the H channel. Almost unsupervised is the method proposed by Du et al. [115], where only the 3D pose of the surgical tool in the first video frame needs to be known, and, based on this the position of the instrument in all subsequent frames is estimated.

5.2.3. Tracking approaches

This section summarizes the key concepts in the current literature for tracking surgical tools over time. Often, this information is processed within the network architecture, for example, by using recurrent layers. Attia et al. [114] present an approach in which the low-level

features resulting from the network’s encoder are processed in four alternating convolutional and recurrent layers and then converted into the final output by the decoder. Also based on the idea of recurrent layers is the method of Yang et al. [121], which uses blocks of recurrent convolutional layers in both the encoder and decoder of its architecture. Adapting the idea of processing recurrent sequences, Lin et al. [118] present a module located between the encoder and decoder of a segmentation network and can be used to temporally and spatially aggregate features of video frames.

In addition to recurrent components, long short-term memory (LSTM) blocks are often incorporated into the network structure. Current work exploits temporal information by processing features at the bottleneck of an encoder–decoder architecture in LSTM blocks [124,129]. Other articles integrate such layers into the decoder of an auxiliary task to improve overall segmentation results [126]. Related publications describe an approach in which the features of successive frames are aggregated by convolutional LSTM layers [127].

In addition to recurrent layers and LSTM mechanisms, determining the motion flow between two successive frames by computing the OF field is a commonly used approach. To this end, Lin et al. [117] present a method that computes the OF as an intermediate step in a multi-stage procedure to determine the potential position of the surgical instrument in the successive video frame. The approach of Sestini

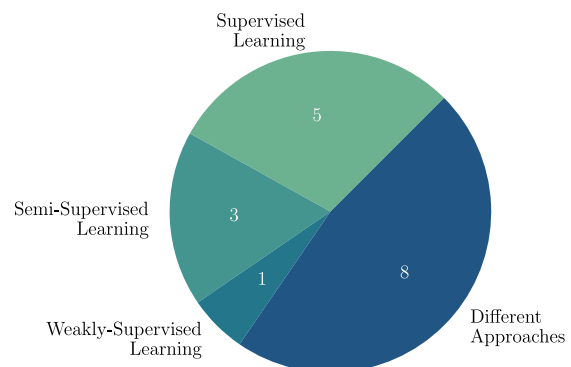


Fig. 8. Amount of relevant papers for semantic segmentation incorporating temporal information divided according to the respective learning strategies used.

Table 7

Semantic segmentation methods incorporating temporal information that have specified processing speeds at inference time. Indicated are the publication, the speed in FPS, the image resolution, the GPU used as well as the number of graphics cards, and the CPU used and the number of CPUs. The publications are sorted in descending order according to the reported inference speed.

Publication	Inf. speed (FPS)	Resolution	GPU	# GPU	CPU	# CPU
Lin et al. (2021) [118]	182	240 × 240	Titan Xp	1	Core-i7-7700K 4.20 GHz	1
	117	360 × 640				
Islam et al. (2021) [126]	42	1024 × 1280	RTX 2080 Ti	1	–	–
Wang et al. (2021) [127]	38	512 × 640	Titan RTX	4	–	–
Agustinos and Voros (2015) [112]	30	556 × 720	No GPU	0	Xeon 2.67 GHz	1
Amini Khoiy et al. (2016) [113]	30	480 × 640	No GPU	0	Core Duo 2.5 GHz	1
		480 × 640,				
Garcia-P.-H. et al. (2016) [116]	30	576 × 720,	GTX Titan X	1	Xeon E5-1650 v3,	1
		[460 × 612,				
		1080 × 1920]			3.50 GHz	
Zhang and Gao (2020) [125]	15	480 × 640	GTX 1080 Ti	1	Core i-7-7700 3.60 GHz	1
Zhao et al. (2021) [123]	4	1024 × 1280	Titan Xp	1	–	–
Zhao et al. (2021) [122]	3	1024 × 1280	Titan Xp	1	–	–

et al. [120] also relies on a multistep procedure in which unsupervised optical-flow segmentation is the first step. For the generation of realistic binary segmentation maps, a generative-adversarial approach is used to learn the mapping between the domain of optical-flow images and the domain of shape-priors. Garcia-Peraza-Herrera et al. [116] present a method that computes an affine transformation between feature points in the last segmented image and feature points in the current image and then applies this affine transformation to the predicted segmentation masks of a CNN. Also based on OF computation is the approach of Jin et al. [128], which uses the network's prediction for the previous image as a reliable prediction for the position and shape of an instrument in the subsequent frame. In their works, Li et al. and Zhao et al. [124,129] use a network that determines the OF based on a pre-trained network. The results are then processed in two parallel branches to jointly apply the network's predictions and associated annotations to subsequent video images.

Online adaptation describes a research approach that involves dynamically adapting existing models trained using an easily accessible source domain and then applying them to different target domains at test time, with only an annotated segmentation mask available for the first frame of the target domain. A contribution by Zhao et al. [123] describes a meta-learning-based dynamic online adaptive learning approach using a two-step procedure. In step one, they train a segmentation network using a meta-learning approach that provides fast adaptable parameters for step two. Then, this network is dynamically adapted to a new video using the first annotated frame in several iterations, employing the output of the previous frame and the updated parameters to generate pseudo-masks. An improvement of this method is presented by Zhao et al. [122] by applying an anchor-oriented online meta-adaptation approach dealing with one-shot instrument segmentation in robotic surgical videos. For this purpose, the meta-training of the segmentation network is modified by an anchor-matching mechanism. At test time, the pseudo-masks used for online supervision are created using the first annotated frame, called the anchor, and inter-frame visual information instead of the outputs of previous images.

Instead of specifying the segmentation mask as the ground truth of a surgical instrument in the first frame of a sequence, approaches exist that use the 3D pose of the tool as the ground truth. Instruments are then tracked by a 2D tracker based on a generalized hough transformation and a probabilistic segmentation model that makes the probability of a pixel belonging to a tool dependent on the segmentation of the previous video frame. The results of this 2D tracker are combined with a 3D tracking algorithm to estimate the 3D pose of the tool [115]. Further methods limit the relevant region considered for the segmentation of a frame to the results of previous images, tracking the joint of the surgical instrument over time [125]. Similar approaches incorporate the results of previous frames in a related manner, identifying candidate bounding boxes in each image, but searching for an instrument exclusively in the boxes related to the position of the tool in the last frame [112]. The

proposed segmentation algorithm from Amini Khoiy et al. [113] also works only within the region of interest (RoI) identified as relevant in the previous frame and propagated to the current one.

5.2.4. Inference speed

As with single-frame segmentation, processing speed at test time plays a key role in the applicability of the proposed methods in real-world scenarios. In total, we identified nine papers that specifically stated the speed of their processes in FPS, presented together with various characteristics in Table 7.

5.2.5. Attention mechanisms

In total, six papers used attention-based techniques in their work. A popular approach is to leverage attention mechanisms within the network architecture. This can be realized by using squeeze & excitation (SE) techniques built into attention-dense recurrent convolutional blocks (ADRCB) in the encoder and in the decoder and into a context fusion block (CFB) between the two parts [121]. The work of Islam et al. [126] relies on improved SE blocks, executing skip competitive spatial and channel squeeze & excitation (SC-scSE) blocks several times in succession in the decoder path. Another approach is the incorporation of attention-based techniques in multi-frame feature aggregation (MFFA) blocks placed between the encoder and decoder [118]. In their presented DMNet, Wang et al. [127] use RNN and self-attention mechanisms in their local memory module to optimally incorporate current temporal information as well as to better localize the currently viewed frame into the overall temporal structure. Another possible application is presented by Jin et al. [128], where they describe an attention-guided module placed in their network architecture that is used multiple times in a pyramid-like structure. In the meta-training flow of their method, Zhao et al. [122] use attention-inspired techniques in the anchor matching mechanism, identifying noisy pixels for foreground and background.

6. Instance segmentation methods

In the following, we describe contributions regarding instance-based segmentation of surgical instruments in endoscopic video images. The structure is analogous to the one presented in Fig. 4 regarding semantic segmentation methods, with domain adaptation being the only deviation from this as no instance-based works could be identified for this category. We first consider approaches focussing on the processing of individual frames, followed by methods incorporating temporal information.

6.1. Single frame segmentation

Within the following, the developments regarding single-image segmentation using instance-based methods are subdivided concerning the topics segmentation type, learning strategies, inference speed, and use of attention mechanisms.

Table 8

Publications that have contributed in the area of single-image instance segmentation of surgical instruments. For each publication, the type of methodology (SV = supervised), whether or not attention mechanisms (Att.) were used in the methodology, and the datasets used are indicated. The works are grouped according to the used segmentation types visualized in Fig. 9.

Publication	Super-vision	Att.	Used datasets										
			EndoVis				Lap. I2I	Sinus Surg.	UCL dVRK	Kvasir Inst.	Robo-Tool	Private	Other
			15	17	18	19							
Shimgekar et al. (2021) [130]	SV												✓
Baby et al. (2023) [131]	SV	✓		✓	✓								
Cerón et al. (2021) [132]	SV	✓				✓							
Cerón et al. (2022) [133]	SV	✓		✓		✓							
Kitaguchi et al. (2022) [134]	SV												✓
Kitaguchi et al. (2022) [135]	SV												✓
Kurmann et al. (2021) [136]	SV			✓									
Kletz et al. (2019) [137]	SV												✓
Kong et al. (2021) [138]	SV			✓									✓
Roß et al. (2021) [29]	SV	✓					✓						
Sun et al. (2022) [139]	SV	✓		✓									

6.1.1. Segmentation type

Fig. 9 illustrates the number of publications per segmentation type and for each existing combination of them. A representation of all papers based on this partitioning can be found in Table 8.

6.1.2. Learning strategies

All work in this area follows the supervised learning approach. However, the methodologies of these contributions can be subdivided into topic-related groups. Kurmann et al. [136] describe a newly developed architecture based on a shared encoder that forwards the detected features of each layer to the corresponding layers of two decoders. The main idea is to first segment the instruments in the image and then classify the instances thus determined.

In addition, recent research has focused on improving the quality of existing network architectures by incorporating novel developments, for example, by adding advanced modules to the backbone and the feature pyramid network (FPN) of an established architecture [132, 133]. Sun et al. [139] also modify the backbone part of a network by adding novel modules, although the basic architecture has a different structure from the ones mentioned above. An improvement of existing architecture is also presented by Kong et al. [138], which realizes this by employing an evolved region proposal network part and anchor optimization. Baby et al. [131] extend existing instance segmentation architectures with an additional classification module, which they call a multi-scale mask-attended classifier. Multi-scale mask attention highlights instrument features and suppresses features from background pixels, resulting in improved instrument classification.

In contrast, other research aims to evaluate the performance of established architectures using newly collected data from specific types of operations [134,137]. In this context, the ability to generalize to unknown data from different types of operations is also a key challenge [135]. An evaluation of various methods on several kinds of

operations is also presented by Roß et al. [29], who examine the concepts and quality of participants' submitted developments on the provided data of their organized challenge, especially concerning the criteria of robustness and generalization ability.

6.1.3. Inference speed

A quantitative evaluation of the speed of their approaches at test time is provided by three works, which are presented in Table 9 together with various characteristics.

6.1.4. Attention mechanisms

The use of attention-based techniques is a central component in the development of instance-based approaches. One variant is to modify established architectures by using criss-cross attention blocks to capture global contextual information [132] or by using convolutional block attention modules instead of criss-cross attention blocks [133]. In addition, attention-oriented techniques are integrated into existing architectures through swin-transformer blocks that act as feature fusion modules localized in the backbone. The operations within these swin-transformer blocks essentially consist of multi-head window self-attention and multi-head shift window self-attention operations [139]. Among the methods submitted by the participating teams in the EndoVis-2019 challenge, two rely on the use of attention-based techniques [29].

6.2. Incorporating temporal information

This section presents publications that have provided new findings concerning instance-based segmentation of surgical instruments in endoscopic images and videos by incorporating temporal context. The structure of this section follows the one described in Section 5.2.

6.2.1. Segmentation type

A breakdown of papers by segmentation type is shown in Fig. 10, and a listing of publications by these categories is given in Table 10.

6.2.2. Learning strategies

All the works employ supervised learning techniques. One approach uses established network architectures that are adapted and extended with respect to the specific use case [140,141]. Other methods rely on several different established architectures, processing the frames of a video sequence in parallel and merging the resulting features in the decoder part of the network [142]. Other work describes an approach using the principles of instance-based segmentation techniques to design a novel network architecture that is based on the parallel prediction of instrument types, their localization, and the determination of their unique identities [143].

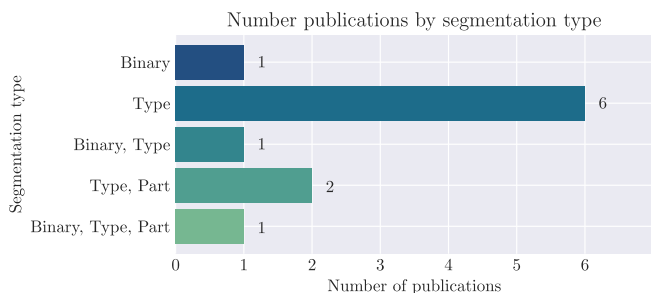


Fig. 9. Number of relevant publications per segmentation type for instance single image segmentation.

Table 9

Instance segmentation methods for single images that have specified processing speeds at inference time. Indicated are the publication, the speed in FPS, the image resolution, the GPU used as well as the number of graphics cards, and the CPU used and the number of CPUs. The publications are sorted in descending order according to the reported inference speed.

Publication	Inf. speed (FPS)	Resolution	GPU	# GPU	CPU	# CPU
Cerón et al. (2021) [132]	49	540 × 960	Tesla P100	1	Xeon E5-2698 v4 2.2 GHz	1
Cerón et al. (2022) [133]	24 - 69	540 × 960	Tesla P100	1	Xeon E5-2698 v4 2.2 GHz	1
Kurmann et al. (2021) [136]	15	512 × 640	RTX 2080 Ti	1	–	–

6.2.3. Tracking approaches

The types of surgical tool tracking over time can be divided into several groups. One approach is to use the frame-by-frame results of successive images by applying tracking techniques to improve the segmentation of subsequent images based on this information. Lee et al. [141] present a method in which they propagate the predicted coordinates of the bounding boxes of surgical instruments from one frame to the next using the deep simple online and real-time tracker (deepSORT) algorithm. Another component of the tracking framework is instrument re-identification, which is needed when instruments leave the field of view or are very close to each other [141]. González et al. [140] describe a method based on an instance segmentation architecture, which they extend by adding a temporal consistency module employing a two-step procedure and thus allows tracking the tools over time.

Other approaches aim at modifying or designing network architectures to process temporal information directly within the model. Current research achieves this through spatio-temporal LSTM layers that model the relationships of video-level features resulting from a network that processes three-dimensional inputs by providing multiple input images simultaneously. For the final segmentation prediction, the outputs of the LSTM layers are further processed by a downstream decoder [142]. In addition to this approach, embedding novel modules into the network architecture is another option for tracking instruments. Recently, Zhao et al. [143] describe two modules explicitly designed to track instruments with huge temporal variations. To achieve this, the authors incorporate the intermediate results of previous frames as well as those of the currently viewed video image and process this information both in an identity-matching module that follows a two-stage structure and in a contrastive query-based learning approach.

6.2.4. Inference speed

The processing speed at inference time is stated with 23 FPS by the work of Zhao et al. [143]. The used datasets have a resolution of 540 × 960 and 1024 × 1280, however, the utilized image size is not explicitly specified. A Titan Xp is employed as hardware, but there is no information about the CPU used.

6.2.5. Attention mechanisms

The method proposed by Zhao et al. [143] is based on a transformer module that further processes the low-level features of the input image

obtained from an encoder network. The module consists of a transformer encoder–decoder network that converts the input image features and query embeddings by applying self- and cross-attention mechanisms to instance embeddings that encode global information about the instruments within the scene. These are then further processed in the contrastive query learning process as well as in the instance fusion module that generates the final classes, bounding box, and mask predictions from these embeddings.

7. Further processing of segmentations

In addition to the segmentation of surgical instruments, approaches for further processing the results are described. Zhang et al. [144] propose an application-oriented method with a specific focus on the endoscope-holding robotic assistant stably holding the endoscope and modifying the position of the endoscopic camera. The authors describe a surgical instrument tracking control method based on visual tracking features in combination with hand-eye coordination, including the feedback of multiple sensors. Accurate binary segmentation and localization of surgical instrument tips are performed to use this information for the autonomous control of the endoscopic field of view. A related approach is published by Gruijthuijsen et al. [145], whose work also describes the interaction between a human surgeon and an autonomous robotic endoscope holder. The authors investigate the applicability of semantically rich instructions of the operator to communicate with the robot. To this end, they explain a technique for determining the positions of instrument tips in which the binary segmentation of surgical tools is of central importance. This information is then processed for visual servo control of the robotic endoscope holder. Li et al. [146] also present an autonomous three-dimensional instrument tracking framework for a robotic laparoscope based on a binocular camera. Based on instrument tip segmentation and stereo matching by a semi-global matching algorithm the depth in the current field of view is determined.

Another approach that combines deep-learning-based segmentation of surgical instruments with visual servo control is described by Cheng et al. [147]. The tips of the instruments are also binarily segmented using an encoder–decoder-based architecture. Subsequently, a robotic system consisting of a robotic arm and a magnetically anchored and actuated endoscope is autonomously moved based on these results.

Zinchenko and Song [148] present another method based on instrument tip segmentation. For the segmentation, rectangular bounding boxes around the instrument tips are first identified by an object detection network, within which the exact structures of the instrument tips are then refined by a network with a different architecture. A difference between the two previously described works arises from the fact that the visualization in the proposed approach is achieved through a simulation in a three-dimensional virtual reality environment. The positioning of the surgical robot is based on the current locations of the instruments and the direction of the surgeon's gaze to determine an optimal new camera image center.

8. Discussion

This chapter discusses the key findings that arise from the literature reviewed. For this purpose, the numerical results of the review obtained using the method described in Section 3 are evaluated first, and an assessment regarding the possible further development of the research



Fig. 10. Number of relevant publications per segmentation type for instance image segmentation incorporating temporal information.

Table 10

Publications that have contributed in the area of instance segmentation of surgical instruments by incorporating temporal information. For each publication, the type of methodology (SV = supervised), whether or not attention mechanisms (Att.) were used in the methodology, and the datasets used are indicated. The works are grouped according to the used segmentation types visualized in Fig. 10.

Publication	Super- vision	Att.	Used datasets										
			EndoVis				Lap. I2I	Sinus Surg.	UCL dVRK	Kvasir Inst.	Robo- Tool	Pri- vate	Ot- her
			15	17	18	19							
Kanakatte et al. (2020) [142]	SV											✓	
González et al. (2020) [140]	SV			✓	✓								
Lee et al. (2020) [141]	SV			✓								✓	
Zhao et al. (2022) [143]	SV	✓		✓	✓								✓

field is presented. This is followed by a consideration of currently publicly available datasets described in more detail in Section 4. For this purpose, the strengths and weaknesses of the existing datasets are highlighted, and potentials for future developments in this area are presented. Subsequently, the identified work is discussed concerning semantic and instance-based segmentation methods. Again, we describe existing strengths and weaknesses and identify promising opportunities for future developments.

8.1. Review methodology

Our search terms focus on the publication titles, leading to a large number of highly specific contributions to the topic of this review. However, there might be more general approaches, which show their results exemplarily also on the public datasets for minimally invasive surgery instrument segmentation and which are not covered by this review, e.g., [149–151].

The number of included papers analyzed in Section 3.2 and presented graphically in Fig. 1 show a clear positive trend regarding the considered time period. On the one hand, this result shows the high relevance of the research area, both in terms of current research topics and practical application areas, and suggests that the research community will continue to grow steadily. On the other hand, the observations of published works lead to the conclusion that the considered research area still has enormous potential for future development in the coming years.

8.2. Public datasets

The availability of high-quality and publicly available datasets represents a central component for the development and validation of novel methods. Furthermore, such datasets provide the basis for reproducible results, which is also essential for the traceability of scientific findings and for establishing the plausibility of results. The segmentation of surgical instruments poses a particular challenge in this context since this application requires polygonal lines to be drawn around the relevant regions within an image to achieve pixel-precise segmentation ground truths masks, requiring a great deal of manual effort, which involves both time and subsequent financial drawbacks. Based on these reasons, it can be assumed that the number of freely accessible datasets is rather limited despite the increasingly active research in this area. Within the 123 relevant publications identified in Section 3.2, only nine different freely available datasets providing endoscopic images or videos are employed, as shown in Fig. 2. It can further be seen here that the number of times these datasets are used varies greatly. The high number of publications that have used these datasets and the fact that the respective datasets of the four MICCAI challenges are ranked among the six most used datasets suggests the high popularity of these data. Furthermore, a correlation can be observed between the timing of dataset publications within the MICCAI challenges and the successfully submitted number of publications depicted in Fig. 1, where the timing of the first publicly accessible dataset provided within the scope of the MICCAI in 2015 conference can be considered as a starting point for an increasingly active research community. These

results further demonstrate the enormous impact that the challenges organized and conducted as part of the annual MICCAI conferences have on the development of new methods.

However, Fig. 2 also shows that a total of 40 different publications use self-collected and annotated data to develop and validate their methods, ranking the group of private datasets second among the most commonly used datasets. This development is associated with several disadvantages since results generated in this way are not reproducible, verification of the results is not possible, and further research based on the used data is excluded for other research groups. Furthermore, the results obtained based on data collected in this way cannot be compared with the results of other approaches which use different data, which makes it much more difficult to classify a presented method about the current state of research. To improve these drawbacks, we would like to encourage future researchers to use publicly accessible and comparable datasets to develop and validate their approaches or to disclose the collected and self-labeled data, making them accessible to other researchers. Having said this, we are aware of legitimate issues regarding data security of personal medical data and financial considerations in third-party funded projects involving the medical device industry.

The datasets shown in Fig. 2 and described in Section 4 also provide information about current shortcomings and possible future developments. Regarding the data based on manually created annotations, it can be seen that in the creation of more recent datasets, there is a stronger focus on incorporating challenges from real-world operations to increase the robustness of developed algorithms. Furthermore, the generalization capability of developed methods to other types of operations or operations performed in other institutions is becoming increasingly important. This development results in the EndoVis-2019 dataset, which currently corresponds to the largest freely accessible annotated dataset used in the publications considered. In the coming years, this trend will surely increase, and it will be exciting to see how the structure and design, as well as the focus on the various real-world challenges, will evolve in the coming years concerning the provision of new datasets.

In addition to traditional approaches in terms of collecting and labeling data, currently published datasets are using other approaches that represent an interesting trend. As described in 4, current work explores methods to minimize manual annotation effort by generating synthetic training data, as presented in the Laparoscopic I2I Translation and RoboTool datasets. Also, the procedure used to generate the UCL dVRK dataset based on movements of the surgical instruments leads to a significantly lower manual label effort and provides a variety of promising opportunities for future developments. Again, there is great potential for designing new datasets in the coming years, supporting and encouraging research and development of new methods in this area.

8.3. Semantic segmentation methods

In the area of semantic segmentation, it can be observed that the majority of publications concern single-frame segmentation of surgical instruments in endoscopic images, ignoring the temporal context. One

reason may be that frame-by-frame segmentation is more in line with the conventional development process, and most available methods are designed for this use case. Furthermore, methods that consider temporal information in processing have to deal with unlabeled images since usually not every video sequence frame is annotated. Novel approaches have to deal with these challenges, resulting in increased complexity of the development process. However, the consideration of successive results in processing offers great potential for new methods.

Regarding the type of segmentation, most methods are based on the binary distinction between instrument and background, regardless of whether approaches for single-frame segmentation or for tracking surgical instruments over time are considered. This is reasonable at first glance, as it allows distinguishing the surgical tools from the background, but upon closer examination introduces some shortcomings. For applications that further process these segmentations and are made for real-world scenarios, distinguishing the different types of instruments is often of great relevance. Usually, different types of instruments have varying fields of application and appear only in certain phases of an operation. In addition, the behavior of downstream algorithms that make decisions based on this information is often directly affected by the type or part of the instrument. Segmentation at the level of instrument parts, however, allows us to determine the detailed position of an instrument in an image by its shaft and tip and to use this information to track tools over time.

With a few exceptions published in the early years of the considered time period, the vast majority of approaches use deep-learning-based techniques for their methods. Within this group of approaches, most methods apply a supervised learning strategy both for frame-by-frame-based algorithms and concerning tracking methods. Here, the ground truth target data is created by manual labeling since domain-specific knowledge about the existing data is often required. This finding is not particularly surprising since supervised learning is also the most commonly used method in many other application domains, as it represents an intuitive and relatively well-studied method for learning a model compared to other learning strategies. However, the reliance on annotated datasets presents a variety of challenges. First, the creation of manual labels is time-consuming and potentially costly, as this process is typically performed by experts. Second, a reasonably large amount of annotated data is usually required to obtain accurate results.

Dealing with these challenges is playing an increasingly important role in current research. Parallels can be identified between currently published methodological approaches and the structure and nature of recently published datasets since a trend towards fewer manually created annotations can be observed. The semi-supervised learning strategy shows great potential for developing new methods since the data to be processed often consists of video recordings, of which only a small fraction is manually annotated and a much larger fraction of unlabeled video images is available. In addition, promising results have been achieved regarding weakly supervised learning in recent years, which can significantly reduce the effort of manual annotation. In both single-image segmentation methods and, in particular, approaches that incorporate the temporal component, some elements of completely unsupervised learning strategies can also be identified in recent work, opening up new possibilities for further developments to reduce the annotation effort. In addition, a central challenge of methods based on annotated data is the transfer to other domains, showing, for example, different types of operations or coming from other institutions. Current research concerning domain adaptation is yielding very promising results, often based on the incorporation of synthetic data, which also reduces the annotation effort. We think this research areas have great potential for further development and will show an increasing impact in the coming years.

Real-time capable processing at inference time is essential for methods to be applicable in real-world scenarios and medical devices. However, awareness of this issue is low in most of the approaches. Only a small fraction of the frame-by-frame segmentation methods focus on

this issue in particular, indicating that generating high-quality results is more important than the fast processing of inputs. In contrast, fast inference time plays a much more important role for methods that consider temporal information. Since segmentation methods can only be used in real-world surgical procedures if they are fast and show high-quality results, it will become more and more important to consider both aspects in the future. Incorporating the temporal component can be a viable approach, as has already been shown in some recent work.

Our review shows that attention-based approaches are equally important in publications on single-image segmentation and in papers on segmentation involving temporal information. Embedding attention mechanisms into network architecture allows new possibilities that are difficult to realize with solely convolutional-based architectures. In some considered works in this review, this leads to an improvement of the results of the previous state-of-the-art. The publication of articles using attention-oriented approaches has followed a clear positive trend in recent years, and it can be expected that this trend will continue in the future, making the utilization of attention layers within the network structure an active research topic.

8.4. Instance segmentation methods

In addition to semantic segmentation methods, the instance-based segmentation techniques described in Section 6 represent another important group of approaches providing several additional benefits. Instance segmentation allows each surgical tool in the image to be assigned a unique identifier that remains unchanged over time, which is not easily achieved with semantic training labels. This feature is particularly useful in surgeries where instruments of the same type occur multiple times in an image to distinguish between these instruments and to track the individual tools independently over time. In our review, we determined that the number of instance-based papers is nevertheless significantly lower than the number of publications relying on semantic segmentation methods. Since the above advantages have a significant impact on the practical applicability of the methods and due to the promising results of existing methods, the field of instance-based approaches represents a research area with high potential in the future.

Differences between instance-based and semantic-based methods can be seen concerning the segmentation types, since in contrast to the semantic variants only one approach for instance segmentation is based on binary segmentation only, and most of the works are specialized to distinguish the different types of instruments. This finding is hardly surprising since the conceptual design of established instance-based network architectures is well suited for this task and highlights one of the strengths of these methods.

Regarding the learning strategies used, the considered instance segmentation methods differ significantly from the semantic ones discussed before. In single-image processing and in methods involving the temporal component, exclusively supervised learning approaches are used. Concerning the previously mentioned disadvantages of this learning strategy, the advanced and more efficient processing of annotated data represents a conceivable future research focus. Another interesting finding is that no synthetically generated or computer-simulated training data is employed in the publications associated with instance segmentation. Analogous to semantic segmentation, this opens up new possibilities for instance segmentation by including data of this type, thus providing an incentive for further research in this area.

The situation regarding the consideration of processing speed in the development of novel methods is similar to that of semantic segmentation. It would be desirable if awareness of this aspect would also increase for instance-based approaches besides the primary goal to improve the segmentation quality.

The popularity of attention-based techniques, previously discussed for semantic segmentation methods, continues here. Some instance-based publications take advantage of diverse attention modules to better incorporate image features, both in frame-by-frame approaches and

in sequence processing based on temporal information. It is expected that also in the field of instance segmentation, the use of attention-based techniques will play a central role in the following years, both as components within conventional convolutional network architectures as well as through the design of completely attention-based networks that do not use convolutional layers at all.

8.5. Further processing of segmentations

In Section 7, we describe papers that further process the segmentation results for controlling a robotic system. These already show the potential existing in high-quality and fast to compute segmentations for practical use in applications based on them. We do not claim to be exhaustive concerning articles dealing with this topic, as this requires a more detailed search that may not be covered by the search terms used in this review. However, we want to draw attention to this issue by showing that there are promising ways to further process segmentation results.

8.6. Summary of challenges and potential future work

Our described findings confirm that methods based on the segmentation of surgical tools have a high value for RAMIS, as evidenced by the rapidly growing number of publications in this field. However, our results also show that many developments rely on self-collected and annotated data, which makes reproducibility of results and further research based on these data impossible. Moreover, few publicly accessible datasets exist that contain real-world challenges. Providing synthetic or simulated datasets represents a promising approach for the future to reduce manual annotation efforts.

Most reviewed articles ignore the temporal context, although its inclusion provides the potential for higher-quality results and faster processing speed. Furthermore, most semantic approaches perform only binary segmentation, which often represents an insufficient level of accuracy for RAMIS. Most publications are based on supervised deep-learning techniques, which means heavy reliance on manually labeled data. Although real-time processing is an essential requirement for using a method in RAMIS, the focus is often on producing high-quality results, and fast processing of inputs is of secondary importance. A comparison of segmentation types shows that current research often relies on semantic methods. Nevertheless, instance-based approaches have advantages, such as unique identification and tracking of surgical instruments over time, even if multiple tools of the same type are present in an image.

9. Conclusion

In this paper, we provided an overview of the current state of the art concerning semantic and instance-based segmentation of surgical instruments in endoscopic images and videos. To do this, we identified datasets commonly used for method development and validation and quantified their use in the literature. We further conducted a systematic search, divided the results concerning semantic and instance-based segmentation methods, and divided the papers within each segmentation type into single-image segmentation and approaches that use temporal information. In addition, we presented approaches for further processing the semantic segmentation results. We provide a discussion regarding the findings of the reviewed literature, identifying existing shortcomings and highlighting the potential for future developments.

Assisting surgeons in MIS through robotic assistance represents an active research area of increasing importance. In this context, purely vision-based methods for localizing surgical instruments in endoscopic images and videos provide the foundation for many procedures with instrument segmentation enabling accurate prediction and, due to technical and methodological advances, can be performed in real time.

CRediT authorship contribution statement

Tobias Rueckert: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft. **Daniel Rueckert:** Supervision, Writing – review & editing. **Christoph Palm:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

- [1] Ara Darzi, Sean Mackay, Recent advances in minimal access surgery, *BMJ* 324 (7328) (2002) 31–34, <http://dx.doi.org/10.1136/bmj.324.7328.31>.
- [2] Ahmed Hammad, André Wirries, Ardavan Ardeshiri, Olexandr Nikiforov, Florian Geiger, Open versus minimally invasive TLIF: literature review and meta-analysis, *J. Orthop. Surg. Res.* 14 (1) (2019) <http://dx.doi.org/10.1186/s13018-019-1266-y>.
- [3] T. de Rooij, J. van Hilst, D. Boerma, R. van Dam, C. van Eijck, M. Gerhards, J. Klaase, G. Kazemier, M. Luyer, O. Busch, M. Besselink, Minimally invasive versus open distal pancreatectomy (LEOPARD): a multicenter patient-blinded randomized controlled trial, *Ann. Surg.* 20 (1) (2018) S293–S294, <http://dx.doi.org/10.1016/j.jhpb.2018.06.280>.
- [4] Pieter C. van der Sluis, Sylvia van der Horst, Anne M. May, Carlo Schippers, Lodewijk A.A. Brokens, Hans C.A. Joore, Christiaan C. Kroese, Nadia Haj Mohammad, Stella Mook, Frank P. Vlegaar, Inne H.M. Borel Rinkes, Jelle P. Ruurda, Richard van Hillegersberg, Robot-assisted minimally invasive thoracoscopic esophagectomy versus open transthoracic esophagectomy for resectable esophageal cancer: A randomized controlled trial, *Ann. Surg.* 269 (4) (2019) 621–630, <http://dx.doi.org/10.1097/sla.0000000000003031>.
- [5] K.H. Fuchs, Minimally invasive surgery, *Endoscopy* 34 (2) (2002) 154–159, <http://dx.doi.org/10.1055/s-2002-19857>.
- [6] Tamas Haidegger, Stefanie Speidel, Danaïl Stoyanov, Richard M. Satava, Robot-assisted minimally invasive surgery – surgical robotics in the data age, *Proc. IEEE* 110 (7) (2022) 835–846, <http://dx.doi.org/10.1109/jproc.2022.3180350>.
- [7] Lena Maier-Hein, Matthias Eisenmann, Duygu Sarikaya, Kenō März, Toby Collins, Anand Malpani, Johannes Fallert, Hubertus Feussner, Stamatia Gianarou, Pietro Mascagni, Hirenkumar Nakawala, Adrian Park, Carla M. Pugh, Danaïl Stoyanov, S. Swaroop Vedula, Kevin Cleary, Gabor Fichtinger, Germain Forestier, Bernard Gibaud, Teodor P. Grantcharov, Makoto Hashizume, Doreen Heckmann-Nötzel, Hannes Götz Kennigott, Ron Kikinis, Lars Mündermann, Nassir Navab, Sinan Onogur, Tobias Roß, Raphael Sznitman, Russell H. Taylor, Minu Dietlinde Tizabi, Martin Wagner, Gregory D. Hager, Thomas Neumuth, Nicolas Padoy, Justin Collins, Ines Gockel, Jan Goedeke, Daniel A. Hashimoto, Luc Joyeux, Kyle Lam, Daniel Richard Leff, Amin Madani, Hani J. Marcus, Ozanan R. Meireles, Alexander Seitel, Dogu Teber, Frank Ückert, Beat P. Müller-Stich, Pierre Jannin, Stefanie Speidel, Surgical data science – from concepts toward clinical translation, *Med. Image Anal.* 76 (2022) 102306, <http://dx.doi.org/10.1016/j.media.2021.102306>.
- [8] Loubna Bouarfa, Oytun Akman, Armin Schneider, Pieter P. Jonker, Jenny Dankelman, In-vivo real-time tracking of surgical instruments in endoscopic video, *Minim. Invasive Ther. Allied Technol.* 21 (3) (2011) 129–134, <http://dx.doi.org/10.3109/13645706.2011.580764>.
- [9] Virginia Mamone, Rosanna Maria Vigliani, Fabrizio Cutolo, Filippo Cavallo, Simone Guadagni, Vincenzo Ferrari, Robust laparoscopic instruments tracking using colored strips, in: 2017 4th International Conference on Augmented Reality, Virtual Reality, and Computer Graphics, AVR, in: Lecture Notes in Computer Science, vol. 10325, Springer International Publishing, 2017, pp. 129–143, http://dx.doi.org/10.1007/978-3-319-60928-7_11.

- [10] Angela Sorriento, Maria Bianca Porfido, Stefano Mazzoleni, Giuseppe Calvosa, Miria Tenucci, Gastone Ciuti, Paolo Dario, Optical and electromagnetic tracking systems for biomedical applications: A critical review on potentialities and limitations, *IEEE Rev. Biomed. Eng.* 13 (2019) 212–232, <http://dx.doi.org/10.1109/rbme.2019.2939091>.
- [11] Yan Wang, Qiyuan Sun, Zhenzhong Liu, Lin Gu, Visual detection and tracking algorithms for minimally invasive surgical instruments: A comprehensive review of the state-of-the-art, *Robot. Auton. Syst.* 149 (2022) 103945, <http://dx.doi.org/10.1016/j.robot.2021.103945>.
- [12] Roi Anteby, Nir Horesh, Shelly Soffer, Yaniv Zager, Yiftach Barash, Imri Amiel, Danny Rosin, Mordechai Gutman, Eyal Klang, Deep learning visual analysis in laparoscopic surgery: a systematic review and diagnostic test accuracy meta-analysis, *Surg. Endosc.* 35 (4) (2021) 1521–1533, <http://dx.doi.org/10.1007/s00464-020-08168-1>.
- [13] Irene Rivas-Blanco, Carlos Jesús Pérez-del-Pulgar, Isabel García-Morales, Victor F. Muñoz, A review on deep learning in minimally invasive surgery, *IEEE Access* 9 (2021) 48658–48678, <http://dx.doi.org/10.1109/ACCESS.2021.3068852>.
- [14] Congmin Yang, Zijian Zhao, Sanyuan Hu, Image-based laparoscopic tool detection and tracking using convolutional neural networks: a review of the literature, *Comput. Assist. Surg.* 25 (1) (2020) 15–28, <http://dx.doi.org/10.1080/24699322.2020.1801842>.
- [15] Liang Qiu, Changsheng Li, Hongliang Ren, Real-time surgical instrument tracking in robot-assisted surgery using multi-domain convolutional neural network, *Healthc. Technol. Lett.* 6 (6) (2019) 159–164, <http://dx.doi.org/10.1049/htl.2019.0068>.
- [16] Zijian Zhao, Zhaorui Chen, Sandrine Voros, Xiaolin Cheng, Real-time tracking of surgical instruments based on spatio-temporal context and deep learning, *Comput. Assist. Surg.* 24 (sup1) (2019) 20–29, <http://dx.doi.org/10.1080/24699322.2018.1560097>.
- [17] Baoru Huang, Anh Nguyen, Siyao Wang, Ziyang Wang, Erik Mayer, David Tuch, Kunal Vyas, Stamatia Giannarou, Daniel S. Elson, Simultaneous depth estimation and surgical tool segmentation in laparoscopic images, *IEEE Trans. Med. Robotics Bionics* 4 (2) (2022) 335–338, <http://dx.doi.org/10.1109/tmrb.2022.3170215>.
- [18] Mobarakol Islam, Yueyuan Li, Hongliang Ren, Learning where to look while tracking instruments in robot-assisted surgery, in: *International Conference on Medical Image Computing and Computer-Assisted Intervention, MICCAI 2019*, Springer International Publishing, 2019, pp. 412–420, http://dx.doi.org/10.1007/978-3-030-32254-0_46.
- [19] Mobarakol Islam, Daniel Anojan Atputharuban, Ravikiran Ramesh, Hongliang Ren, Real-time instrument segmentation in robotic surgery using auxiliary supervised deep adversarial learning, *IEEE Robot. Autom. Lett.* 4 (2) (2019) 2188–2195, <http://dx.doi.org/10.1109/lra.2019.2900854>.
- [20] Debesh Jha, Sharib Ali, Nikhil Kumar Tomar, Michael A. Riegler, Dag Johansen, Håvard D. Johansen, Pål Halvorsen, Exploring deep learning methods for real-time surgical instrument segmentation in laparoscopy, in: *2021 IEEE EMBS International Conference on Biomedical and Health Informatics, BHI, IEEE, 2021*, pp. 1–4, <http://dx.doi.org/10.1109/BHI50953.2021.9508610>.
- [21] Daniil Pakhomov, Nassir Navab, Searching for efficient architecture for instrument segmentation in robotic surgery, in: *Medical Image Computing and Computer Assisted Intervention, MICCAI 2020*, in: *Lecture Notes in Computer Science*, vol. 12263, Springer International Publishing, 2020, pp. 648–656, http://dx.doi.org/10.1007/978-3-030-59716-0_62.
- [22] Mark Rodrigues, Michael Mayo, Panos Patros, Surgical tool datasets for machine learning research: A survey, *Int. J. Comput. Vis.* 130 (9) (2022) 2222–2248, <http://dx.doi.org/10.1007/s11263-022-01640-6>.
- [23] David Bouget, Max Allan, Danail Stoyanov, Pierre Jannin, Vision-based and marker-less surgical tool detection and tracking: a review of the literature, *Med. Image Anal.* 35 (2017) 633–654, <http://dx.doi.org/10.1016/j.media.2016.09.003>.
- [24] Shubhangi Nema, Leena Vachhani, Surgical instrument detection and tracking technologies: Automating dataset labeling for surgical skill assessment, *Front. Robotics AI* 9 (2022) <http://dx.doi.org/10.3389/frobt.2022.1030846>.
- [25] Max Allan, Alexey Shvets, Thomas Kurmann, Zichen Zhang, Rahul Duggal, Yun-Hsuan Su, Nicola Rieke, Iro Laina, Niveditha Kalavakonda, Sebastian Bodenstedt, Luis C. García-Peraza, Wenqi Li, Vladimir Iglovikov, Huoling Luo, Jian Yang, Danail Stoyanov, Lena Maier-Hein, Stefanie Speidel, Mahdi Azizian, 2017 Robotic instrument segmentation challenge, 2019, CoRR abs/1902.06426, [arXiv:1902.06426](http://arxiv.org/abs/1902.06426).
- [26] Sebastian Bodenstedt, Max Allan, Anthony Agustinos, Xiaofei Du, Luis C. García-Peraza-Herrera, Hannes Kennigott, Thomas Kurmann, Beat P. Müller-Stich, Sébastien Ourselin, Daniil Pakhomov, Raphael Sznitman, Marvin Teichmann, Martin Thoma, Tom Vercauteren, Sandrine Voros, Martin Wagner, Pamela Wochner, Lena Maier-Hein, Danail Stoyanov, Stefanie Speidel, Comparative evaluation of instrument segmentation and tracking methods in minimally invasive surgery, 2018, CoRR abs/1805.02475, [arXiv:1805.02475](http://arxiv.org/abs/1805.02475).
- [27] Max Allan, Satoshi Kondo, Sebastian Bodenstedt, Stefan Leger, Rahim Kadkhodamohammadi, Imanol Luengo, Félix Fuentes-Hurtado, Evangello Flouty, Ahmed Kedir Mohammed, Marius Pedersen, Avinash Kori, Alex Varghese, Ganapathy Krishnamurthi, David Rauber, Robert Mendel, Christoph Palm, Sophia Bano, Gunther Saibro, Chi-Sheng Shih, Hsun-An Chiang, Juntang Zhuang, Junlin Yang, Vladimir Iglovikov, Anton Dobrenkii, Madhu Reddiboina, Anubhav Reddy, Xingtong Liu, Cong Gao, Mathias Unberath, Mahdi Azizian, Danail Stoyanov, Lena Maier-Hein, Stefanie Speidel, 2018 Robotic scene segmentation challenge, 2020, CoRR abs/2001.11190, [arXiv:2001.11190](http://arxiv.org/abs/2001.11190).
- [28] Debesh Jha, Sharib Ali, Krister Emanuels, Steven Alexander Hicks, Vajira Thambawita, Enrique Garcia-Ceja, Michael A. Riegler, Thomas de Lange, Peter Thelin Schmidt, Håvard D. Johansen, Dag Johansen, Pål Halvorsen, Kvasir-instrument: Diagnostic and therapeutic tool segmentation dataset in gastrointestinal endoscopy, in: *2021 27th MultiMedia Modeling International Conference, MMM*, in: *Lecture Notes in Computer Science*, vol. 12573, Springer International Publishing, 2021, pp. 218–229, http://dx.doi.org/10.1007/978-3-030-67835-7_19.
- [29] Tobias Roß, Annika Reinke, Peter M. Full, Martin Wagner, Hannes Kennigott, Martin Apitz, Hellena Hempe, Diana Mîndroc-Filimon, Patrick Scholz, Thuy Nuong Tran, Pierangela Bruno, Pablo Arbeláez, Gui-Bin Bian, Sebastian Bodenstedt, Jon Lindström Bolmgren, Laura Bravo Sánchez, Hua-Bin Chen, Cristina González, Dong Guo, Pål Halvorsen, Pheng-Ann Heng, Enes Hosgor, Zeng-Guang Hou, Fabian Isensee, Debesh Jha, Tingting Jiang, Yueming Jin, Kadir Kirtaç, Sabrina Kletz, Stefan Leger, Zhixuan Li, Klaus H. Maier-Hein, Zhen-Liang Ni, Michael A. Riegler, Klaus Schoeffmann, Ruohua Shi, Stefanie Speidel, Michael Stenzel, Isabell Twick, Guotai Wang, Jiacheng Wang, Liansheng Wang, Lu Wang, Yujie Zhang, Yan-Jie Zhou, Lei Zhu, Manuel Wiesenfarth, Annette Kopp-Schneider, Beat P. Müller-Stich, Lena Maier-Hein, Comparative validation of multi-instance instrument segmentation in endoscopy: Results of the ROBUST-MIS 2019 challenge, *Med. Image Anal.* 70 (2021) 101920, <http://dx.doi.org/10.1016/j.media.2020.101920>.
- [30] Fangbo Qin, Shan Lin, Yangming Li, Randall A. Bly, Kris S. Moe, Blake Hannaford, Towards better surgical instrument segmentation in endoscopic vision: Multi-angle feature aggregation and contour supervision, *IEEE Robot. Autom. Lett.* 5 (4) (2020) 6639–6646, <http://dx.doi.org/10.1109/LRA.2020.3009073>.
- [31] Shan Lin, Fangbo Qin, Yangming Li, Randall A. Bly, Kris S. Moe, Blake Hannaford, I.C.-GAN: image-to-image translation based on generative adversarial network for endoscopic images, in: *2020 IEEE/RISJ International Conference on Intelligent Robots and Systems, IROS, IEEE, 2020*, pp. 2914–2920, <http://dx.doi.org/10.1109/IROS45743.2020.9341556>.
- [32] Micha Pfeiffer, Isabel Funke, Maria R. Robu, Sebastian Bodenstedt, Leon Strenger, Sandy Engelhardt, Tobias Roß, Matthew J. Clarkson, Kurinchi Gurusamy, Brian R. Davidson, Lena Maier-Hein, Carina Riediger, Thilo Welsch, Jürgen Weitz, Stefanie Speidel, Generating large labeled data sets for laparoscopic image processing tasks using unpaired image-to-image translation, in: *Medical Image Computing and Computer Assisted Intervention, MICCAI 2019*, in: *Lecture Notes in Computer Science*, vol. 11768, Springer International Publishing, 2019, pp. 119–127, http://dx.doi.org/10.1007/978-3-030-32254-0_14.
- [33] Emanuele Colleoni, Philip J. Edwards, Danail Stoyanov, Synthetic and real inputs for tool segmentation in robotic surgery, in: *Medical Image Computing and Computer Assisted Intervention, MICCAI 2020*, in: *Lecture Notes in Computer Science*, vol. 12263, Springer International Publishing, 2020, pp. 700–710, http://dx.doi.org/10.1007/978-3-030-59716-0_67.
- [34] Luis C. García-Peraza-Herrera, Lucas Fidon, Claudia D’Ettorre, Danail Stoyanov, Tom Vercauteren, Sébastien Ourselin, Image compositing for segmentation of surgical tools without manual annotations, *IEEE Trans. Med. Imaging* 40 (5) (2021) 1450–1460, <http://dx.doi.org/10.1109/TMI.2021.3057884>.
- [35] Lena Maier-Hein, Sven Mersmann, Daniel Kondermann, Sebastian Bodenstedt, Alexandro Sanchez, Christian Stock, Hannes Götz Kennigott, Matthias Eisenmann, Stefanie Speidel, Can masses of non-experts train highly accurate image classifiers? – A crowdsourcing approach to instrument segmentation in laparoscopic images, in: *Medical Image Computing and Computer-Assisted Intervention, MICCAI 2014*, in: *Lecture Notes in Computer Science*, vol. 8674, Springer International Publishing, 2014, pp. 438–445, http://dx.doi.org/10.1007/978-3-319-10470-6_55.
- [36] David Bouget, Rodrigo Benenson, Mohamed Omran, Laurent Riffaud, Bernt Schiele, Pierre Jannin, Detecting surgical tools by modelling local appearance and global shape, *IEEE Trans. Med. Imaging* 34 (12) (2015) 2603–2617, <http://dx.doi.org/10.1109/TMI.2015.2450831>.
- [37] W.-Y. Hong, Chia-Lung Kao, Yi-Hung Kuo, J.-R. Wang, W.-L. Chang, Chi-Sheng Shih, CholecSeg8k: A semantic segmentation dataset for laparoscopic cholecystectomy based on cholec80, 2020, CoRR abs/2012.12453, [arXiv:2012.12453](http://arxiv.org/abs/2012.12453).
- [38] HeiSurf, Surgical workflow analysis and full scene segmentation, 2021, <https://www.synapse.org/#!Synapse:syn25101790/wiki/608802>.
- [39] Md. Kamrul Hasan, Lilian Calvet, Navid Rabbani, Adrien Bartoli, Detection, segmentation, and 3D pose estimation of surgical tools using convolutional neural networks and algebraic geometry, *Med. Image Anal.* 70 (2021) 101994, <http://dx.doi.org/10.1016/j.media.2021.101994>.

- [40] Maria Grammatikopoulou, Evangello Flouty, Abdulrahim Kadkhodamohammadi, Gwenolé Quellec, Andre Chow, Jean Nehme, Imanol Luengo, Danail Stoyanov, CaDIS: Cataract dataset for surgical RGB-image segmentation, *Med. Image Anal.* 71 (2021) 102053, <http://dx.doi.org/10.1016/j.media.2021.102053>.
- [41] Ziyi Wang, Bo Lu, Yonghao Long, Fangxun Zhong, Tak Hong Cheung, Qi Dou, Yunhui Liu, AutoLaparo: A new dataset of integrated multi-tasks for image-guided surgical automation in laparoscopic hysterectomy, in: *Medical Image Computing and Computer Assisted Intervention, MICCAI 2022*, in: *Lecture Notes in Computer Science*, vol. 13437, Springer International Publishing, 2022, pp. 486–496, http://dx.doi.org/10.1007/978-3-031-16449-1_46.
- [42] Andru Putra Twinanda, Sherif Shehata, Didier Mutter, Jacques Marescaux, Michel de Mathelin, Nicolas Padoy, EndoNet: A deep architecture for recognition tasks on laparoscopic videos, *IEEE Trans. Med. Imaging* 36 (1) (2017) 86–97, <http://dx.doi.org/10.1109/TMI.2016.2593957>.
- [43] Debapriya Banik, Kaushiki Roy, Debotosh Bhattacharjee, EM-Net: An efficient M-Net for segmentation of surgical instruments in colonoscopy frames, *Nord. Mach. Intell.* 1 (1) (2021) 14–16, <http://dx.doi.org/10.5617/nmi.9122>.
- [44] YuCheng Chou, Automatic polyp and instrument segmentation in MedAI-2021, *Nord. Mach. Intell.* 1 (1) (2021) 17–19, <http://dx.doi.org/10.5617/nmi.9125>.
- [45] Wangkheirakpam Reema Devi, Sudipta Roy, Khelchandra Thongam, Chiranjiv Chingangbam, Multi-scale dilated fusion network (MSDFN) for automatic instrument segmentation, *J. Comput. Sci. Technol. Stud.* 4 (1) (2022) 66–72, <http://dx.doi.org/10.32996/jcsts.2022.4.1.7>.
- [46] Yu Dong, Hongbo Wang, Jingjing Luo, Zhiping Lai, Fuhao Wang, Jiawei Wang, Semantic segmentation of surgical instruments based on enhanced multi-scale receptive field, *J. Phys. Conf. Ser.* 2003 (2021) 012006, <http://dx.doi.org/10.1088/1742-6596/2003/1/012006>.
- [47] Adrian Galdran, Polyp and surgical instrument segmentation with double encoder-decoder networks, *Nord. Mach. Intell.* 1 (1) (2021) 5–7, <http://dx.doi.org/10.5617/nmi.9107>.
- [48] Yue Guo, Changjian Ye, Yongchang Zhang, Wenhao He, Conditional relativistic GAN for fast part segmentation of surgical instruments, in: *CAIBDA 2022; 2nd International Conference on Artificial Intelligence, Big Data and Algorithms, VDE, 2022*, pp. 1–6.
- [49] S.M. Kamrul Hasan, Richard A. Simon, Cristian A. Linte, Segmentation and removal of surgical instruments for background SceneVisualization from endoscopic / laparoscopic video, in: *Medical Imaging 2021: Image-Guided Procedures, Robotic Interventions, and Modeling*, Vol. 11598, SPIE, 2021, pp. 55–61, <http://dx.doi.org/10.1117/12.2580668>.
- [50] Wenhao He, Haitao Song, Yue Guo, Guibin Bian, Yuejie Sun, Xiaowei Zhou, Xiaonan Wang, Multiscale matters for part segmentation of instruments in robotic surgery, *IET Image Process.* 14 (13) (2020) 3215–3222, <http://dx.doi.org/10.1049/iet-ipc.2020.0320>.
- [51] S.M. Kamrul Hasan, Cristian A. Linte, U-NetPlus: A modified encoder-decoder U-net architecture for semantic and instance segmentation of surgical instruments from laparoscopic images, in: *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, IEEE, 2019*, pp. 7205–7211, <http://dx.doi.org/10.1109/embc.2019.8856791>.
- [52] Arvind Keprate, Sumit Pandey, Kvasir-instruments and polyp segmentation using UNet, *Nord. Mach. Intell.* 1 (1) (2021) 26–28, <http://dx.doi.org/10.5617/nmi.9130>.
- [53] Iro Laina, Nicola Rieke, Christian Ruppert, Josué Page Vizcaíno, Abouzar Eslami, Federico Tombari, Nassir Navab, Concurrent segmentation and localization for tracking of surgical instruments, in: *Medical Image Computing and Computer-Assisted Intervention, MICCAI 2017*, Springer International Publishing, 2017, pp. 664–672, http://dx.doi.org/10.1007/978-3-319-66185-8_75.
- [54] Zhen-Liang Ni, Gui-Bin Bian, Xiao-Liang Xie, Zeng-Guang Hou, Xiao-Hu Zhou, Yan-Jie Zhou, RASNet: Segmentation for tracking surgical instruments in surgical videos using refined attention segmentation network, in: *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, IEEE, 2019*, pp. 5735–5738, <http://dx.doi.org/10.1109/embc.2019.8856495>.
- [55] Rishav Kumar Rajak, Ashar Mirza, Segmentation of polyp instruments using UNet based deep learning model, *Nord. Mach. Intell.* 1 (1) (2021) 44–46, <http://dx.doi.org/10.5617/nmi.9145>.
- [56] Wenting Shen, Yaonan Wang, Min Liu, Jiazheng Wang, Renjie Ding, Zhe Zhang, Erik Meijering, Branch aggregation attention network for robotic surgical instrument segmentation, *IEEE Trans. Med. Imaging* (2023) <http://dx.doi.org/10.1109/tmi.2023.3288127>.
- [57] Takuya Suzuki, Keisuke Doman, Yoshito Mekada, Depth estimation for instrument segmentation from a single laparoscopic video toward laparoscopic surgery, in: *Proceedings of the 2019 International Conference on Intelligent Medicine and Image Processing, IMIP, ACM, 2019*, pp. 21–24, <http://dx.doi.org/10.1145/3332340.3332347>.
- [58] V. Vishal, C. Udaya Kumar, Robotic surgical instrument segmentation using dual global attention upsampling, in: *2018 32nd Conference on Neural Information Processing Systems, NIPS, 2018*.
- [59] Xiaoyan Wang, Luyao Wang, Xingyu Zhong, Cong Bai, Xiaojie Huang, Ruiyi Zhao, Ming Xia, Pal-Net: A modified U-Net of reducing semantic gap for surgical instrument segmentation, *IET Image Process.* 15 (12) (2021) 2959–2969, <http://dx.doi.org/10.1049/ipr2.12283>.
- [60] Yiming Wang, Zhongxi Qiu, Yan Hu, Hao Chen, Fangfu Ye, Jiang Liu, Surgical instrument segmentation based on multi-scale and multi-level feature network, in: *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society, EMBC, IEEE, 2021*, pp. 2672–2675, <http://dx.doi.org/10.1109/EMBC46164.2021.9629891>.
- [61] Yiming Wang, Yan Hu, Junyong Shen, Xiaoqing Zhang, Heng Li, Zhongxi Qiu, Fangfu Ye, Jiang Liu, CGBA-net: context-guided bidirectional attention network for surgical instrument segmentation, *Int. J. Comput. Assist. Radiol. Surg.* (2023) <http://dx.doi.org/10.1007/s11548-023-02906-1>.
- [62] Lei Yang, Yuge Gu, Gui-Bin Bian, Yanhong Liu, An attention-guided network for surgical instrument segmentation from endoscopic images, *Comput. Biol. Med.* 151 (Part) (2022) 106216, <http://dx.doi.org/10.1016/j.combiomed.2022.106216>.
- [63] Lei Yang, Yuge Gu, Guibin Bian, Yanhong Liu, TMF-Net: A transformer-based multiscale fusion network for surgical instrument segmentation from endoscopic images, *IEEE Trans. Instrum. Meas.* 72 (2022) 1–15, <http://dx.doi.org/10.1109/tim.2022.3225922>.
- [64] Lei Yang, Yuge Gu, Guibin Bian, Yanhong Liu, MAF-Net: A multi-scale attention fusion network for automatic surgical instrument segmentation, *Biomed. Signal Process. Control* 85 (2023) 104912, <http://dx.doi.org/10.1016/j.bspc.2023.104912>.
- [65] Lei Yang, Hongyong Wang, Yuge Gu, Guibin Bian, Yanhong Liu, Hongnian Yu, TMA-Net: A transformer-based multi-scale attention network for surgical instrument segmentation, *IEEE Trans. Med. Robotics Bionics* 5 (2) (2023) 323–334, <http://dx.doi.org/10.1109/tmr.2023.3269856>.
- [66] Michael Yeung, Attention U-Net ensemble for interpretable polyp and instrument segmentation, *Nord. Mach. Intell.* 1 (1) (2021) 47–49, <http://dx.doi.org/10.5617/nmi.9157>.
- [67] Lingtao Yu, Pengcheng Wang, Xiaoyan Yu, Yusheng Yan, Yongqiang Xia, A holistically-nested U-net: Surgical instrument segmentation based on convolutional neural network, *J. Digit. Imaging* 33 (2) (2020) 341–347, <http://dx.doi.org/10.1007/s10278-019-00277-1>.
- [68] Xiaowei Zhou, Yue Guo, Wenhao He, Haitao Song, Hierarchical attentional feature fusion for surgical instrument segmentation, in: *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society, EMBC, IEEE, 2021*, pp. 3061–3065, <http://dx.doi.org/10.1109/EMBC46164.2021.9630553>.
- [69] Mobarakol Islam, V.S. Vibashan, Hongliang Ren, AP-MTL: Attention pruned multi-task learning model for real-time instrument detection and segmentation in robot-assisted surgery, in: *2020 IEEE International Conference on Robotics and Automation, ICRA, IEEE, 2020*, pp. 8433–8439, <http://dx.doi.org/10.1109/ICRA40945.2020.9196905>.
- [70] Dimitrios Psychogiou, Evangelos Mazomenos, Francisco Vasconcelos, Danail Stoyanov, MSDESIS: Multi-task stereo disparity estimation and surgical instrument segmentation, *IEEE Trans. Med. Imaging* 41 (11) (2022) 3218–3230, <http://dx.doi.org/10.1109/tmi.2022.3181229>.
- [71] Kevin Huang, Digesh Chitrakar, Wenfan Jiang, Isabella Yung, Yun-Hsuan Su, Surgical tool segmentation with pose-informed morphological polar transform of endoscopic images, *J. Med. Robotics Res.* 7 (02n03) (2022) 2241003, <http://dx.doi.org/10.1142/s2424905x22410033>.
- [72] Wanwan Han, Guanghui Yue, Lvying Duan, Xue Bai, Jingfeng Du, Tianwei Zhou, Tianfu Wang, CEID: Benchmark dataset for designing segmentation algorithms of instruments used in colorectal endoscopy, in: *International Conference on Image and Graphics, Springer, 2021*, pp. 618–629, http://dx.doi.org/10.1007/978-3-030-87358-5_50.
- [73] Niveditha Kalavakonda, Blake Hannaford, Zeeshan Qazi, Laligam Sekhar, Autonomous neurosurgical instrument segmentation using end-to-end learning, in: *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, CVPRW, IEEE, 2019*, pp. 514–516, <http://dx.doi.org/10.1109/cvprw.2019.00076>.
- [74] Manish Sahu, Anirban Mukhopadhyay, Stefan Zachow, Simulation-to-real domain adaptation with teacher-student learning for endoscopic instrument segmentation, *Int. J. Comput. Assist. Radiol. Surg.* 16 (5) (2021) 849–859, <http://dx.doi.org/10.1007/s11548-021-02383-4>.
- [75] Ricardo Sanchez-Matilla, Maria Robu, Imanol Luengo, Danail Stoyanov, Scalable joint detection and segmentation of surgical instruments with weak supervision, in: *Medical Image Computing and Computer Assisted Intervention, MICCAI 2021*, in: *Lecture Notes in Computer Science*, vol. 12902, Springer International Publishing, 2021, pp. 501–511, http://dx.doi.org/10.1007/978-3-030-87196-3_47.
- [76] Ange Lou, Kareem Tawfik, Xing Yao, Ziteng Liu, Jack Noble, Min-max similarity: A contrastive semi-supervised deep learning network for surgical tools segmentation, *IEEE Trans. Med. Imaging* (2023) <http://dx.doi.org/10.1109/tmi.2023.3266137>.

- [77] Cristian da Costa Rocha, Nicolas Padoy, Benoit Rosa, Self-supervised surgical tool segmentation using kinematic information, in: 2019 International Conference on Robotics and Automation, ICRA, IEEE, 2019, pp. 8720–8726, <http://dx.doi.org/10.1109/icra.2019.8794334>.
- [78] Luis C. García-Peraza-Herrera, Wenqi Li, Lucas Fidon, Caspar Gruijthuisen, Alain Devreker, George Attilakos, Jan Deprest, Emmanuel Vander Poorten, Danail Stoyanov, Tom Vercauteren, et al., ToolNet: Holistically-nested real-time segmentation of robotic surgical tools, in: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, IEEE, 2017, pp. 5717–5722, <http://dx.doi.org/10.1109/iros.2017.8206462>.
- [79] Luis C. García-Peraza-Herrera, Lucas Fidon, Claudia D'Ettoire, Danail Stoyanov, Tom Vercauteren, Sébastien Ourselin, Image compositing for segmentation of surgical tools without manual annotations, IEEE Trans. Med. Imaging 40 (5) (2021) 1450–1460, <http://dx.doi.org/10.1109/TMI.2021.3057884>.
- [80] Saúl Alexis Heredia Pérez, Murilo Marques Marinho, Kanako Harada, Mamoru Mitsushih, The effects of different levels of realism on the training of CNNs with only synthetic images for the semantic segmentation of robotic instruments in a head phantom, Int. J. Comput. Assist. Radiol. Surg. 15 (8) (2020) 1257–1265, <http://dx.doi.org/10.1007/s11548-020-02185-0>.
- [81] Megha Kalia, Tajwar Abrar Aleef, Nassir Navab, Peter C. Black, Septimiu E. Salcudean, Co-generation and segmentation for generalized surgical instrument segmentation on unlabelled data, in: Medical Image Computing and Computer Assisted Intervention, MICCAI 2021, in: Lecture Notes in Computer Science, vol. 12904, Springer International Publishing, 2021, pp. 403–412, http://dx.doi.org/10.1007/978-3-030-87202-1_39.
- [82] Eung-Joo Lee, William Plishker, Xinyang Liu, Shuvra S Bhattacharyya, Raj Shekhar, Weakly supervised segmentation for real-time surgical tool tracking, Healthc. Technol. Lett. 6 (6) (2019) 231–236, <http://dx.doi.org/10.1049/hlt.2019.0083>.
- [83] Eung-Joo Lee, William Plishker, Xinyang Liu, Timothy Kane, Shuvra S. Bhattacharyya, Raj Shekhar, Segmentation of surgical instruments in laparoscopic videos: training dataset generation and deep-learning-based framework, in: Medical Imaging 2019: Image-Guided Procedures, Robotic Interventions, and Modeling, Vol. 10951, SPIE, 2019, pp. 461–469, <http://dx.doi.org/10.1117/12.2512994>.
- [84] George Leifman, Amit Aides, Tomer Golany, Daniel Freedman, Ehud Rivlin, Pixel-accurate segmentation of surgical tools based on bounding box annotations, in: 2022 26th International Conference on Pattern Recognition, ICPR, IEEE, 2022, pp. 5096–5103, <http://dx.doi.org/10.1109/ICPR56361.2022.9956530>.
- [85] Daniil Pakhomov, Wei Shen, Nassir Navab, Towards unsupervised learning for instrument segmentation in robotic surgery with cycle-consistent adversarial networks, in: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, IEEE, 2020, pp. 8499–8504, <http://dx.doi.org/10.1109/iros45743.2020.9340816>.
- [86] Dóra Papp, Renáta Nagyné Elek, Tamás Haidegger, Surgical tool segmentation on the JIGSAWS dataset for autonomous image-based skill assessment, in: 2022 IEEE 10th Jubilee International Conference on Computational Cybernetics and Cyber-Medical Systems, ICCS, IEEE, 2022, pp. 000049–000056, <http://dx.doi.org/10.1109/iccc202255925.2022.9922713>.
- [87] Fangbo Qin, Yangming Li, Yun-Hsuan Su, De Xu, Blake Hannaford, Surgical instrument segmentation for endoscopic vision with data fusion of CNN prediction and kinematic pose, in: 2019 International Conference on Robotics and Automation, ICRA, IEEE, 2019, pp. 9821–9827, <http://dx.doi.org/10.1109/icra.2019.8794122>.
- [88] Manish Sahu, Ronja Strömsdörfer, Anirban Mukhopadhyay, Stefan Zachow, Endo-Sim2Real: Consistency learning-based domain adaptation for instrument segmentation, in: Medical Image Computing and Computer Assisted Intervention, MICCAI 2020, in: Lecture Notes in Computer Science, vol. 12263, Springer International Publishing, 2020, pp. 784–794, http://dx.doi.org/10.1007/978-3-030-59716-0_75.
- [89] Yun-Hsuan Su, Issac Huang, Kevin Huang, Blake Hannaford, Comparison of 3D surgical tool segmentation procedures with robot kinematics prior, in: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, IEEE, 2018, pp. 4411–4418, <http://dx.doi.org/10.1109/iros.2018.8594428>.
- [90] Yun-Hsuan Su, Kevin Huang, Blake Hannaford, Real-time vision-based surgical tool segmentation with robot kinematics prior, in: 2018 International Symposium on Medical Robotics, ISMR, IEEE, 2018, <http://dx.doi.org/10.1109/ismr.2018.8333305>.
- [91] An Wang, Mobarakol Islam, Mengya Xu, Hongliang Ren, Rethinking surgical instrument segmentation: A background image can be all you need, in: Medical Image Computing and Computer Assisted Intervention, MICCAI 2022, in: Lecture Notes in Computer Science, vol. 13437, Springer International Publishing, 2022, pp. 355–364, http://dx.doi.org/10.1007/978-3-031-16449-1_34.
- [92] Zixin Yang, Richard Simon, Cristian Linte, A weakly supervised learning approach for surgical instrument segmentation from laparoscopic video sequences, in: Medical Imaging 2022: Image-Guided Procedures, Robotic Interventions, and Modeling, Vol. 12034, SPIE, 2022, pp. 412–417, <http://dx.doi.org/10.1117/12.2610778>.
- [93] Zhongkai Zhang, Benoît Rosa, Florent Nageotte, Surgical tool segmentation using generative adversarial networks with unpaired training data, IEEE Robotics Autom. Lett. 6 (4) (2021) 6266–6273, <http://dx.doi.org/10.1109/LRA.2021.3092302>.
- [94] Vighnesh Birodkar, Zhichao Lu, Siyang Li, Vivek Rathod, Jonathan Huang, The surprising impact of mask-head architecture on novel class segmentation, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, IEEE, 2021, pp. 7015–7025, <http://dx.doi.org/10.1109/iccv48922.2021.00693>.
- [95] Jie Liu, Xiaoqing Guo, Yixuan Yuan, Prototypical interaction graph for unsupervised domain adaptation in surgical instrument segmentation, in: Medical Image Computing and Computer Assisted Intervention, MICCAI 2021, in: Lecture Notes in Computer Science, vol. 12903, Springer International Publishing, 2021, pp. 272–281, http://dx.doi.org/10.1007/978-3-030-87199-4_26.
- [96] Zhen-Liang Ni, Gui-Bin Bian, Zeng-Guang Hou, Xiao-Hu Zhou, Xiao-Liang Xie, Zhen Li, Attention-guided lightweight network for real-time segmentation of robotic surgical instruments, in: 2020 IEEE International Conference on Robotics and Automation, ICRA, IEEE, 2020, pp. 9939–9945, <http://dx.doi.org/10.1109/ICRA40945.2020.9197425>.
- [97] Zhen-Liang Ni, Gui-Bin Bian, Guan'an Wang, Xiao-Hu Zhou, Zeng-Guang Hou, Hua-Bin Chen, Xiao-Liang Xie, Pyramid attention aggregation network for semantic segmentation of surgical instruments, in: Proceedings of the AAAI Conference on Artificial Intelligence, Association for the Advancement of Artificial Intelligence (AAAI), 2020, pp. 11782–11790, <https://ojs.aaai.org/index.php/AAAI/article/view/6850>.
- [98] Zhen-Liang Ni, Gui-Bin Bian, Guan'an Wang, Xiao-Hu Zhou, Zeng-Guang Hou, Xiao-Liang Xie, Zhen Li, Yu-Han Wang, BARNet: Bilinear attention network with adaptive receptive fields for surgical instrument segmentation, in: Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI, International Joint Conferences on Artificial Intelligence Organization, 2020, pp. 832–838, <http://dx.doi.org/10.24963/ijcai.2020/116>.
- [99] Zhen-Liang Ni, Xiao-Hu Zhou, Guan'an Wang, Wen-Qian Yue, Zhen Li, Gui-Bin Bian, Zeng-Guang Hou, SurgiNet: Pyramid attention aggregation and class-wise self-distillation for surgical instrument segmentation, Med. Image Anal. 76 (2022) 102310, <http://dx.doi.org/10.1016/j.media.2021.102310>.
- [100] Mengchen Xue, Lixu Gu, Surgical instrument segmentation method based on improved MobileNetV2 network, in: 2021 6th International Symposium on Computer and Information Processing Technology, ISCIPT, IEEE, 2021, pp. 744–747, <http://dx.doi.org/10.1109/iscipt53667.2021.00157>.
- [101] Jakob K.H. Andersen, Kim Lindberg Schwaner, Thiusius Rajeeth Savarimuthu, Real-time segmentation of surgical tools and needle using a mobile-U-Net, in: 2021 20th International Conference on Advanced Robotics, ICAR, IEEE, 2021, pp. 148–154, <http://dx.doi.org/10.1109/ICAR53236.2021.9659326>.
- [102] Shubhangi Nema, Leena Vachhani, Unpaired deep adversarial learning for multi-class segmentation of instruments in robot-assisted surgical videos, Int. J. Med. Robotics Comput. Assist. Surg. 19 (4) (2023) e2514, <http://dx.doi.org/10.1002/rocs.2514>.
- [103] Takuya Ozawa, Yuichiro Hayashi, Hirohisa Oda, Masahiro Oda, Takayuki Kitasaka, Nobuyoshi Takeshita, Masaaki Ito, Kensaku Mori, Synthetic laparoscopic video generation for machine learning-based surgical instrument segmentation from real laparoscopic video and virtual surgical instruments, Comput. Methods Biomech. Biomed. Eng. Imaging Vis. 9 (3) (2021) 225–232, <http://dx.doi.org/10.1080/21681163.2020.1835560>.
- [104] Yanwen Sun, Bo Pan, Yili Fu, Lightweight deep neural network for real-time instrument semantic segmentation in robot assisted minimally invasive surgery, IEEE Robotics Autom. Lett. 6 (2) (2021) 3870–3877, <http://dx.doi.org/10.1109/LRA.2021.3066956>.
- [105] Emanuele Colleoni, Dimitris Psychogios, Beatrice van Amsterdam, Francisco Vasconcelos, Danail Stoyanov, SSIS-Seg: Simulation-supervised image synthesis for surgical instrument segmentation, IEEE Trans. Med. Imaging 41 (11) (2022) 3074–3086, <http://dx.doi.org/10.1109/TMI.2022.3178549>.
- [106] Tahir Mahmood, Se Woon Cho, Kang Ryoung Park, DSRD-Net: Dual-stream residual dense network for semantic segmentation of instruments in robot-assisted surgery, Expert Syst. Appl. 202 (2022) 117420, <http://dx.doi.org/10.1016/j.eswa.2022.117420>.
- [107] Daniil Pakhomov, Vittal Premachandran, Max Allan, Mahdi Azizian, Nassir Navab, Deep residual learning for instrument segmentation in robotic surgery, in: 2019 10th International Machine Learning in Medical Imaging (MLMI) Workshop, in: Lecture Notes in Computer Science, vol. 11861, Springer International Publishing, 2019, pp. 566–573, http://dx.doi.org/10.1007/978-3-030-32692-0_65.
- [108] Jie Liu, Xiaoqing Guo, Yixuan Yuan, Graph-based surgical instrument adaptive segmentation via domain-common knowledge, IEEE Trans. Med. Imaging 41 (3) (2022) 715–726, <http://dx.doi.org/10.1109/TMI.2021.3121138>.
- [109] Alexey A. Shvets, Alexander Rakhlin, Alexandr A. Kalinin, Vladimir I. Iglovikov, Automatic instrument segmentation in robot-assisted surgery using deep learning, in: 2018 17th IEEE International Conference on Machine Learning and Applications, ICMLA, Cold Spring Harbor Laboratory, 2018, pp. 624–628, <http://dx.doi.org/10.1101/275867>.

- [110] Jun-Yan Zhu, Taesung Park, Phillip Isola, Alexei A. Efros, Unpaired image-to-image translation using cycle-consistent adversarial networks, in: 2017 IEEE International Conference on Computer Vision, ICCV, IEEE, 2017, pp. 2242–2251, <http://dx.doi.org/10.1109/ICCV.2017.244>.
- [111] Emanuele Colleoni, Danail Stoyanov, Robotic instrument segmentation with image-to-image translation, *IEEE Robotics Autom. Lett.* 6 (2) (2021) 935–942, <http://dx.doi.org/10.1109/LRA.2021.3056354>.
- [112] Anthony Agustinos, Sandrine Voros, 2D/3D real-time tracking of surgical instruments based on endoscopic image processing, in: *Computer-Assisted and Robotic Endoscopy*, Springer International Publishing, 2015, pp. 90–100, http://dx.doi.org/10.1007/978-3-319-29965-5_9.
- [113] Keyvan Amini Khoiy, Alireza Mirbagheri, Farzam Farahmand, Automatic tracking of laparoscopic instruments for autonomous control of a cameraman robot, *Minim. Invasive Ther. Allied Technol.* 25 (3) (2016) 121–128, <http://dx.doi.org/10.3109/13645706.2016.1141101>.
- [114] Mohammed Hassan Attia, Alireza Mirbagheri, Saeid Nahavandi, Hamed Asadi, Surgical tool segmentation using a hybrid deep CNN-RNN auto encoder-decoder, in: 2017 IEEE International Conference on Systems, Man, and Cybernetics, SMC, IEEE, 2017, pp. 3373–3378, <http://dx.doi.org/10.1109/SMC.2017.8123151>.
- [115] Xiaofei Du, Maximilian Allan, Alessio Dore, Sebastien Ourselin, David Hawkes, John D. Kelly, Danail Stoyanov, Combined 2D and 3D tracking of surgical instruments for minimally invasive and robotic-assisted surgery, *Int. J. Comput. Assist. Radiol. Surg.* 11 (6) (2016) 1109–1119, <http://dx.doi.org/10.1007/s11548-016-1393-4>.
- [116] Luis C. García-Peraza-Herrera, Wenqi Li, Caspar Gruijthuisen, Alain Devreker, George Attilakos, Jan Deprest, Emmanuel B. Vander Poorten, Danail Stoyanov, Tom Vercauteren, Sébastien Ourselin, Real-time segmentation of non-rigid surgical tools based on deep learning and tracking, in: *Computer-Assisted and Robotic Endoscopy*, Vol. 10170, Springer International Publishing, 2016, pp. 84–95, http://dx.doi.org/10.1007/978-3-319-54057-3_8.
- [117] Shan Lin, Fangbo Qin, Randall A. Bly, Kris S. Moe, Blake Hannaford, Automatic sinus surgery skill assessment based on instrument segmentation and tracking in endoscopic video, in: 2019 First International Multiscale Multimodal Medical Imaging (MMMI) Workshop, in: *Lecture Notes in Computer Science*, vol. 11977, Springer International Publishing, 2019, pp. 93–100, http://dx.doi.org/10.1007/978-3-030-37969-8_12.
- [118] Shan Lin, Fangbo Qin, Haonan Peng, Randall A. Bly, Kris S. Moe, Blake Hannaford, Multi-frame feature aggregation for real-time instrument segmentation in endoscopic video, *IEEE Robotics Autom. Lett.* 6 (4) (2021) 6773–6780, <http://dx.doi.org/10.1109/Lra.2021.3096156>.
- [119] Daochang Liu, Yuhui Wei, Tingting Jiang, Yizhou Wang, Rulin Miao, Fei Shan, Ziyu Li, Unsupervised surgical instrument segmentation via anchor generation and semantic diffusion, in: *Medical Image Computing and Computer Assisted Intervention*, MICCAI 2020, Springer International Publishing, 2020, pp. 657–667, http://dx.doi.org/10.1007/978-3-030-59716-0_63.
- [120] Luca Sestini, Benoit Rosa, Elena De Momi, Giancarlo Ferrigno, Nicolas Padoy, FUN-SIS: A fully unsupervised approach for surgical instrument segmentation, *Med. Image Anal.* 85 (2023) 102751, <http://dx.doi.org/10.1016/j.media.2023.102751>.
- [121] Lei Yang, Yuge Gu, Guibin Bian, Yanhong Liu, DRR-Net: A dense-connected residual recurrent convolutional network for surgical instrument segmentation from endoscopic images, *IEEE Trans. Med. Robotics Bionics* 4 (3) (2022) 696–707, <http://dx.doi.org/10.1109/tmrb.2022.3193420>.
- [122] Zixu Zhao, Yueming Jin, Junming Chen, Bo Lu, Chi-Fai Ng, Yun-Hui Liu, Qi Dou, Pheng-Ann Heng, Anchor-guided online meta adaptation for fast one-shot instrument segmentation from robotic surgical videos, *Med. Image Anal.* 74 (2021) 102240, <http://dx.doi.org/10.1016/j.media.2021.102240>.
- [123] Zixu Zhao, Yueming Jin, Bo Lu, Chi-Fai Ng, Qi Dou, Yun-Hui Liu, Pheng-Ann Heng, One to many: Adaptive instrument segmentation via meta learning and dynamic online adaptation in robotic surgical video, in: 2021 IEEE International Conference on Robotics and Automation, ICRA, IEEE, 2021, pp. 13553–13559, <http://dx.doi.org/10.1109/ICRA48506.2021.9561690>.
- [124] Yaoqian Li, Caizi Li, Weixin Si, Preserving the temporal consistency of video sequences for surgical instruments segmentation, in: 2021 3rd International Conference on Intelligent Medicine and Image Processing, IMIP, ACM, 2021, pp. 78–82, <http://dx.doi.org/10.1145/3468945.3468958>.
- [125] Jiayi Zhang, Xin Gao, Object extraction via deep learning-based marker-free tracking framework of surgical instruments for laparoscope-holder robots, *Int. J. Comput. Assist. Radiol. Surg.* 15 (8) (2020) 1335–1345, <http://dx.doi.org/10.1007/s11548-020-02214-y>.
- [126] Mobarak Islam, V.S. Vibashan, Chwee Ming Lim, Hongliang Ren, ST-MTL: Spatio-temporal multitask learning model to predict scanpath while tracking instruments in robotic surgery, *Med. Image Anal.* 67 (2021) 101837, <http://dx.doi.org/10.1016/j.media.2020.101837>.
- [127] Jiacheng Wang, Yueming Jin, Liansheng Wang, Shuntian Cai, Pheng-Ann Heng, Jing Qin, Efficient global-local memory for real-time instrument segmentation of robotic surgical video, in: *International Conference on Medical Image Computing and Computer-Assisted Intervention*, MICCAI 2021, Springer International Publishing, 2021, pp. 341–351, http://dx.doi.org/10.1007/978-3-030-87202-1_33.
- [128] Yueming Jin, Keyun Cheng, Qi Dou, Pheng-Ann Heng, Incorporating temporal prior from motion flow for instrument segmentation in minimally invasive surgery video, in: *Medical Image Computing and Computer Assisted Intervention*, MICCAI 2019, in: *Lecture Notes in Computer Science*, 11768, Springer International Publishing, 2019, pp. 440–448, http://dx.doi.org/10.1007/978-3-030-32254-0_49.
- [129] Zixu Zhao, Yueming Jin, Xiaojie Gao, Qi Dou, Pheng-Ann Heng, Learning motion flows for semi-supervised instrument segmentation from robotic surgical video, in: *Medical Image Computing and Computer Assisted Intervention*, MICCAI 2020, Springer International Publishing, 2020, pp. 679–689, http://dx.doi.org/10.1007/978-3-030-59716-0_65.
- [130] Soorva Ram Shingekar, Preetham Reddy Pathi, V. Santhi, Voice based segmentation of laparoscopic surgical tools and its image enhancement, in: 2021 Innovations in Power and Advanced Computing Technologies, I-PACT, IEEE, 2021, <http://dx.doi.org/10.1109/i-pact52855.2021.9696600>.
- [131] Britty Baby, Daksh Thapar, Mustafa Chasmai, Tamajit Banerjee, Kunal Dargan, Ashish Suri, Subhashis Banerjee, Chetan Arora, From forks to forceps: A new framework for instance segmentation of surgical instruments, in: *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, IEEE, 2023, pp. 6191–6201, <http://dx.doi.org/10.1109/wacv56688.2023.00613>.
- [132] Juan Carlos Ángeles Cerón, Leonardo Chang, Gilberto Ochoa Ruiz, Sharib Ali, Assessing YOLACT++ for real time and robust instance segmentation of medical instruments in endoscopic procedures, in: 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society, EMBC, IEEE, 2021, pp. 1824–1827, <http://dx.doi.org/10.1109/embc46164.2021.9629914>.
- [133] Juan Carlos Ángeles Cerón, Gilberto Ochoa Ruiz, Leonardo Chang, Sharib Ali, Real-time instance segmentation of surgical instruments using attention and multi-scale feature fusion, *Med. Image Anal.* 81 (2022) 102569, <http://dx.doi.org/10.1016/j.media.2022.102569>.
- [134] Daichi Kitaguchi, Younae Lee, Kazuyuki Hayashi, Kei Nakajima, Shigehiro Kojima, Hiro Hasegawa, Nobuyoshi Takeshita, Kensaku Mori, Masaaki Ito, Development and validation of a model for laparoscopic colorectal surgical instrument recognition using convolutional neural network-based instance segmentation and videos of laparoscopic procedures, *JAMA Netw. Open* 5 (8) (2022) e2226265, <http://dx.doi.org/10.1001/jamanetworkopen.2022.26265>.
- [135] Daichi Kitaguchi, Toru Fujino, Nobuyoshi Takeshita, Hiro Hasegawa, Kensaku Mori, Masaaki Ito, Limited generalizability of single deep neural network for surgical instrument segmentation in different surgical environments, *Sci. Rep.* 12 (1) (2022) 12575, <http://dx.doi.org/10.1038/s41598-022-16923-8>.
- [136] Thomas Kurmann, Pablo Márquez-Neila, Max Allan, Sebastian Wolf, Raphael Sznitman, Mask then classify: multi-instance segmentation for surgical instruments, *Int. J. Comput. Assist. Radiol. Surg.* 16 (7) (2021) 1227–1236, <http://dx.doi.org/10.1007/s11548-021-02404-2>.
- [137] Sabrina Kletz, Klaus Schoeffmann, Jenny Benois-Pineau, Heinrich Husslein, Identifying surgical instruments in laparoscopy using deep learning instance segmentation, in: 2019 International Conference on Content-Based Multimedia Indexing, CBMI, IEEE, 2019, pp. 1–6, <http://dx.doi.org/10.1109/cbmi.2019.8877379>.
- [138] Xiaowen Kong, Yueming Jin, Qi Dou, Ziyi Wang, Zerui Wang, Bo Lu, Erbao Dong, Yun-Hui Liu, Dong Sun, Accurate instance segmentation of surgical instruments in robotic surgery: model refinement and cross-dataset evaluation, *Int. J. Comput. Assist. Radiol. Surg.* 16 (9) (2021) 1607–1614, <http://dx.doi.org/10.1007/s11548-021-02438-6>.
- [139] Xinan Sun, Yuelin Zou, Shuxin Wang, He Su, Bo Guan, A parallel network utilizing local features and global representations for segmentation of surgical instruments, *Int. J. Comput. Assist. Radiol. Surg.* (2022) 1–11, <http://dx.doi.org/10.1007/s11548-022-02687-z>.
- [140] Cristina González, Laura Bravo-Sánchez, Pablo Arbelaez, ISINet: An instance-based approach for surgical instrument segmentation, in: *Medical Image Computing and Computer Assisted Intervention*, MICCAI 2020, Springer International Publishing, 2020, pp. 595–605, http://dx.doi.org/10.1007/978-3-030-59716-0_57.
- [141] Dongheon Lee, Hyeongwon Yu, Hyungju Kwon, Hyoun-Joong Kong, Kyu Eun Lee, Hee Chan Kim, Evaluation of surgical skills during robotic surgery by deep learning-based multiple surgical instrument tracking in training and actual operations, *J. Clin. Med.* 9 (6) (2020) 1964, <http://dx.doi.org/10.3390/jcm9061964>.
- [142] Aparna Kanakatte, Akshaya Ramaswamy, Jayavardhana Gubbi, Avik Ghose, Balaramalidhar Purushothaman, Surgical tool segmentation and localization using spatio-temporal deep network, in: 2020 42nd Annual International Conferences of the IEEE Engineering in Medicine and Biology Society, EMBC, IEEE, 2020, pp. 1658–1661, <http://dx.doi.org/10.1109/embc44109.2020.9176676>.
- [143] Zixu Zhao, Yueming Jin, Pheng-Ann Heng, TraSeTR: track-to-segment transformer with contrastive query for instance-level instrument segmentation in robotic surgery, in: 2022 International Conference on Robotics and Automation, ICRA, IEEE, 2022, pp. 11186–11193, <http://dx.doi.org/10.1109/icra46639.2022.9811873>.
- [144] Chi Zhang, Wangru Zhu, Jianqing Peng, Yu Han, Wanquan Liu, Visual servo control of endoscope-holding robot based on multi-objective optimization: System modeling and instrument tracking, *SSRN Electron. J.* 211 (2023) 112658, <http://dx.doi.org/10.2139/ssrn.4174849>.

- [145] Caspar Gruijthuisen, Luis C. García-Peraza-Herrera, Gianni Borghesan, Dominiek Reynaerts, Jan Deprest, Sébastien Ourselin, Tom Vercauteren, Emmanuel B. Vander Poorten, Robotic endoscope control via autonomous instrument tracking, *Front. Robotics AI* 9 (2022) 832208, <http://dx.doi.org/10.3389/frobt.2022.832208>.
- [146] Jian Li, Yisen Huang, Xue Zhang, Ke Xie, Yitian Xian, Xiao Luo, Philip Wai Yan Chiu, Zheng Li, An autonomous surgical instrument tracking framework with a binocular camera for a robotic flexible laparoscope, *IEEE Robot. Autom. Lett.* 8 (7) (2023) 4291–4298, <http://dx.doi.org/10.1109/lra.2023.3281934>.
- [147] Truman Cheng, Weibing Li, Wing Yin Ng, Yisen Huang, Jixiu Li, Calvin Sze Hang Ng, Philip Wai Yan Chiu, Zheng Li, Deep learning assisted robotic magnetic anchored and guided endoscope for real-time instrument tracking, *IEEE Robotics Autom. Lett.* 6 (2) (2021) 3979–3986, <http://dx.doi.org/10.1109/LRA.2021.3066834>.
- [148] Kateryna Zinchenko, Kai-Tai Song, Autonomous endoscope robot positioning using instrument segmentation with virtual reality visualization, *IEEE Access* 9 (2021) 72614–72623, <http://dx.doi.org/10.1109/ACCESS.2021.3079427>.
- [149] Robert Mendel, David Rauber, Luis A. de Souza Jr., João P. Papa, Christoph Palm, Error-correcting mean-teacher: Corrections instead of consistency-targets applied to semi-supervised medical image segmentation, *Comput. Biol. Med.* 154 (2023) 106585, <http://dx.doi.org/10.1016/j.compbiomed.2023.106585>.
- [150] Zhen-Liang Ni, Gui-Bin Bian, Zhen Li, Xiao-Hu Zhou, Rui-Qi Li, Zeng-Guang Hou, Space squeeze reasoning and low-rank bilinear feature fusion for surgical image segmentation, *IEEE J. Biomed. Health Inf.* 26 (7) (2022) 3209–3217, <http://dx.doi.org/10.1109/jbhi.2022.3154925>.
- [151] Bowen Wang, Liangzhi Li, Yuta Nakashima, Ryo Kawasaki, Hajime Nagahara, Yasushi Yagi, Noisy-LSTM: Improving temporal awareness for video semantic segmentation, *IEEE Access* 9 (2021) 46810–46820, <http://dx.doi.org/10.1109/access.2021.3067928>.