ST(OR)^2: Spatio-Temporal Object Level Reasoning for Activity Recognition in the Operating Room

Author name(s) withheld EMAIL(S) WITHHELD
Address withheld

Editors: Under Review for MIDL 2023

Abstract

Surgical robotics holds much promise for improving patient safety and clinician experience in the Operating Room (OR). However, it also comes with new challenges, requiring strong team coordination and effective OR management. Automatic detection of surgical activities is a key requirement for developing AI-based intelligent tools to tackle these challenges. The current state-of-the-art surgical activity recognition methods however operate on image-based representations and depend on large-scale labeled datasets whose collection is time-consuming and resource-expensive. This work proposes a new sample-efficient and object-based approach for surgical activity recognition in the OR. Our method focuses on the geometric arrangements between clinicians and surgical devices, thus utilizing the significant object interaction dynamics in the OR. We conduct experiments in a low-data regime study for long video activity recognition. We also benchmark our method against other object-centric approaches on clip-level action classification and show superior performance.

Keywords: OR Workflow Analysis, OR Surgical Activity Recognition, Object Level Reasoning, Human-object interaction

1. Introduction

Modern-day surgeries are continually evolving from an artisanal craft to a high-tech discipline. Minimally invasive surgery, particularly robotic-assisted surgery (RAS), has revamped the traditional surgical approaches, reducing postoperative recovery and hospitalization time (Sheetz KH, 2020). Still, some barriers are limiting its overall adoption. As these procedures require the clinicians to operate in a spatially constrained and technically challenging environment, it can result in poor intraoperative team communication (Schiff et al., 2016) and hindrance in the OR workflow (Catchpole et al., 2015; Kanji et al., 2021).

The recent advent of surgical data science (SDS) (Maier-Hein et al., 2022) aims to build AI-based OR assistance systems to tackle these challenges. The emerging new approaches, such as semantic scene understanding of OR (Li et al., 2020), activity analysis in robot-assisted surgery (Sharghi et al., 2020; Schmidt et al., 2021), surgical workflow recognition (Zhang et al., 2021; Kadkhodamohammadi et al., 2021; Twinanda et al., 2017b), and radiation risk monitoring during interventional surgical procedures (Rodas et al., 2016), show the potential of such systems in streamlining clinical workflow processes and supporting real-time decision-making (Vercauteren et al., 2019; Padoy, 2019; Mascagni and Padoy, 2021).

One of the core technologies developed in this direction is surgical activity recognition (SAR), which aims to segment surgical videos into phases temporally. This coarse temporal

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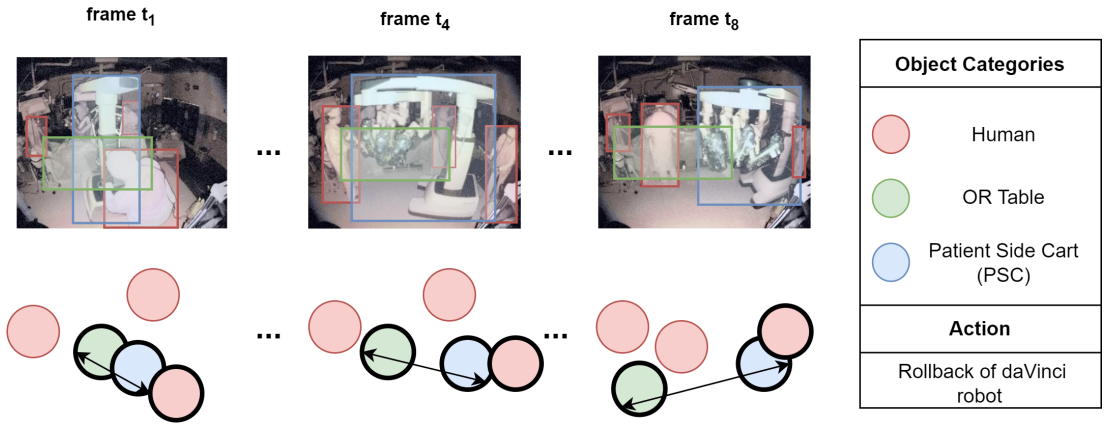

Figure 1: Example video of an action class, in this case "daVinci Rollback". Our method focuses on geometric interactions of semantically identified objects. Here the proximity of one of the clinicians with the PSC and the fact they are both getting away from the OR table is a strong clue to predict the correct action.

segmentation is a first step towards measuring OR efficiency for robot and resource usage, designing better workflows, and improving human-machine collaboration. Inspired by recent advances in action recognition in the general computer vision community (Carreira and Zisserman, 2017; Feichtenhofer et al., 2018; Bertasius et al., 2021; Patrick et al., 2021), SAR uses clip-based models to segment the temporal phases in surgical videos (Sharghi et al., 2020; Schmidt et al., 2021; He et al., 2022; Hajj et al., 2018; Czempiel et al., 2020; Twinanda et al., 2017a). Although powerful, these methods work on either clip-level representations or global image-based feature representations and do not explicitly embed local object-based feature representations. This lack of structured representation burdens data efficiency, requiring a model to use large-scale annotated datasets for generalization. This is a crucial concern, especially in surgical data analysis, due to the high cost and effort necessary to gather a sufficient number of well-annotated videos.

This work proposes a novel OR surgical activity recognition approach that exploits object-level dynamics. The idea of our approach bears its root in developmental psychology (Tenenbaum et al., 2011) and its adoption in computer vision (Materzynska et al., 2019). The development psychology theories agree on object-centric reasoning being a core constituent of human-level common sense. It has been shown that decomposing a scene into meaningful units, including foreground and background objects, can benefit from the numerous advantages of abstract symbolic representation. These include data efficiency, the ability to reason over semantically defined objects, and compositionality for better generalization with less annotated data. Objects being the atomic units of physical interactions, it seems reasonable to discretize surgical scene representations at the object level.

Inspired by these, our approach employs geometrically grounded surgical scene constituents, i.e., bounding boxes of clinicians and OR objects, to build a Spatio-Temporal geometric interaction graph. As shown in Figure 1, the object-centric modeling of the surgical scene and its temporal evolution provide strong cues to predict correct surgical action.

We use simple multi-layer perceptron networks to reason over the object-centric interaction graph for action recognition. This turns out to be the key to showing the generalizability of our method with less labeled data. Our experiment shows that by using as few as 5% of action labels, our approach reaches 54.2 mAP, surpassing the global feature-based baseline by 15%. The paper's contributions are two-fold:

1. We propose a new geometrically grounded object-centric approach for SAR.
2. We achieve significantly better results against the baseline methods across different percentages of labeled supervision.

2. Related Work

2.1. Surgical Video Understanding

Surgical activity recognition has been widely studied in laparoscopic videos and ophthalmological videos, mainly due to the availability of public datasets such as Cholec80 (Twinanda et al., 2017a) or Cataracts100 (Hajj et al., 2018). State-of-the-art approaches to videos capturing complete procedures all adopt two-stage training. The first stage serves as a feature extractor on individual frames, whereas the second stage encapsulates long-range temporal patterns. In TECNO (Czempiel et al., 2020) proposed to use a TCN (Lea et al., 2016) on top of ResNet18 (He et al., 2015) features for each frame to temporally segment videos of cholecystectomy. (Murali et al., 2022) recently proposed a graph based approach for critical view of safety assessment using geometric disposition of anatomical structures.

Our work falls into the scope of holistic operating room video understanding (Srivastav et al., 2019, 2018; Luo et al., 2018; Sharghi et al., 2020; Li et al., 2020; Chakraborty et al., 2013; Issenhuth et al., 2019). The pioneering works on this type of data have been proposed for hand hygiene compliance and human pose estimation for clinicians in the operating room. An important aspect of these datasets is privacy preservation through the use of low-resolution color (Srivastav et al., 2020), or depth (Srivastav et al., 2019) images.

In 4D-OR, (Özsoy et al., 2022) introduced a new dataset with densely annotated 3D scene graphs in an orthopedic OR. They exploit geometric interactions and annotated interactions to determine clinicians' roles.

In the work proposed by (Sharghi et al., 2020), authors introduced an OR Activity Recognition dataset for workflow monitoring, they proposed a two-stage approach with a 3D CNN coupled with an LSTM (Hochreiter and Schmidhuber, 1997). Their work was later on extended by (Schmidt et al., 2021), who proposed to use an attention layer to merge information from multiple views of the OR. Recently, (He et al., 2022) proposed an extensive benchmark of temporal models on this same dataset. (Jamal and Mohareri, 2022) proposes an unsupervised pre-training approach using multi-modal data for OR understanding under low-data regimes. In this work, we want to address the data efficiency issues by introducing a new object-centric model that utilizes the spatial configuration of objects in the OR.

2.2. Object-centric Video Models

Video understanding benchmarks such as action recognition on large publicly available datasets have recently seen a significant improvement with the development of approaches based on 3D CNN (Carreira and Zisserman, 2017; Feichtenhofer, 2020; Feichtenhofer et al.,

2018) and Video Transformer (Bertasius et al., 2021; Patrick et al., 2021). Those methods albeit powerful do not explicitly exploit spatio-temporal human-object interaction cues.

Recently, many approaches to make use of relational reasoning have been proposed in the video-understanding community. To spatially ground features from a 3D CNN, STRG (Wang and Gupta, 2018) proposes a class-agnostic approach using a temporal graph over densely sampled regions of interest in video frames. In STIN (Materzynska et al., 2019), the authors build an object graph using both position and category information of tracked objects to recognize actions in a compositional setting. In ORViT (Herzig et al., 2022), authors proposed a fully transformer-based approach to reason over object information in two ways: by attending to pooled object features similarly to STRG (Wang and Gupta, 2018) and by encoding object trajectories at different intermediate layers using tracked bounding boxes of objects. A detailed study of the transferability of object-centric action recognition to other downstream tasks was lately proposed by (Zhang et al., 2022).

3. Methods

We propose Spatio-Temporal Object-level Reasoning in the Operating Room (ST(OR)^2) for OR surgical activity recognition. ST(OR)^2 takes as input the 2-d bounding boxes extracted from a T frame-long clip subsampled by two. We use the bounding box geometric information and the semantic information about each object class to build our graph. We use our spatio-temporal object graph to reason over the objects' relative locations to recognize clip actions based on interaction dynamics. This backbone serves as the first stage of our long video segmentation, as it allows us to extract reliable features.

In the second stage, we use the features extracted from our clip-based model to train a temporal sequence model to capture long-range dependencies in the videos.

3.1. Object-level Representation

To train our backbone, we sample a short T-frame long clips from each phase of the longer OR surgical videos. Each object appearing in those frames will serve as a node of our graph. Inspired by STIN (Materzynska et al., 2019), each node will be associated with specific features grounded on the position and category of the object (cf Figure2).

Person/Object Detection We infer bounding boxes for all videos using two Cascade Mask RCNN (Cai and Vasconcelos, 2018) with a ConvNext backbone (Liu et al., 2022) pretrained on OR images for human and RAS-specific objects. We will use N bounding boxes for each frame of the videos. If a frame has fewer than N boxes, the remaining boxes are pad with zeros.

Spatial Position Embedding We represent object position using their bounding box coordinates as a 4-d vector containing center coordinates and the width and height of the box. This 4-d vector is then forwarded to a multi-layer perceptron (MLP), to obtain a d-dimension embedding.

$$\sigma_{i,t} = MLP_{SPE}(box_{i,t}) \quad i \in \{1, \dots, N\},\ t \in \{1, \dots, T\} \tag{1}$$

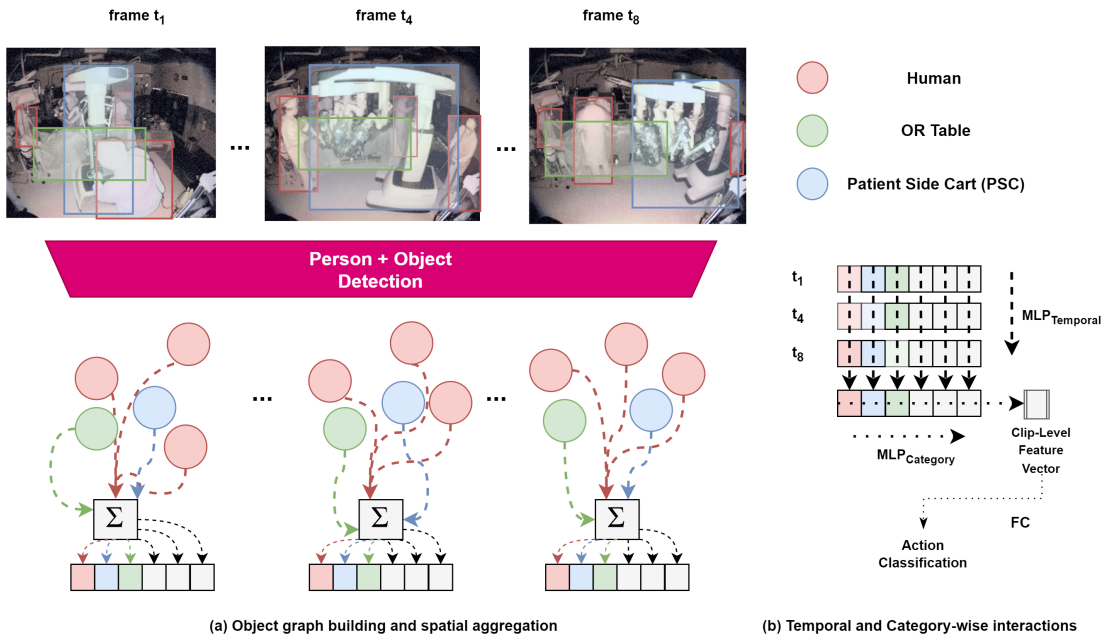

Figure 2: Architecture of our method, we first build our object graph and aggregate features category-wise. In the second step, we reason over time for each category and then we reason over categories to obtain a clip-level feature vector for action classification.

Category Embedding We use the knowledge about the classes of objects to enhance each node's representation. Each of those C classes will be associated with a d-dimension learnable embedding, that is randomly initialized from an independent multivariate normal distribution.

$$class_{i,t} = c \in \{1, \dots, C\} \quad \kappa_{i,t} = Embed_c \quad i \in \{1, \dots, N\},\ t \in \{1, \dots, T\} \tag{2}$$

Both spatial position embedding and category embedding are concatenated and passed through an MLP to obtain a fused representation for each node of the graph.

$$x_{i,t} = MLP_{Fusion}(\sigma_{i,t} || \kappa_{i,t}) \quad i \in \{1, \dots, N\},\ t \in \{1, \dots, T\} \tag{3}$$

3.2. Spatio-Temporal Reasoning

Category-wise Aggregation We aggregate features of objects belonging to the same category by summing them together. This alleviates any need for tracking different instances of the same class across frames, but also discards instance-wise specific information for humans.

$$\varphi_{c,t} = \sum_{class_{i,t}=c} x_{i,t} \quad c \in \{1, \dots, C\},\ t \in \{1, \dots, T\} \tag{4}$$

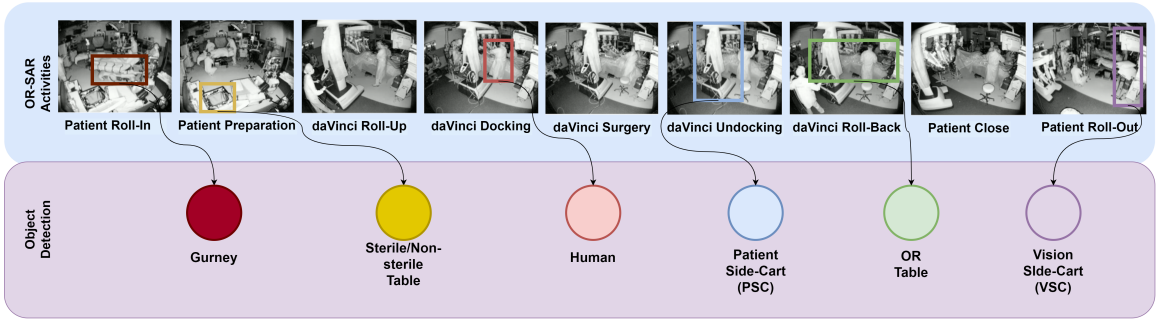

Figure 3: Overview of the OR SAR dataset, with ten clinically relevant activities and six OR-specific objects annotated.

Temporal-Category Interaction Module Using the aggregated features for each object category, we first carry out temporal reasoning across categories after concatenating the $\varphi_{c,t}$ features for each frame t of the clip.

$$\varphi_c = MLP_{Temp}(\varphi_{c,1}||...||\varphi_{c,T}) \quad c \in \{1, \ldots, C\} \tag{5}$$

Once we obtain a feature vector representing the temporal evolution of each object category, we perform category-wise reasoning over the concatenated features of each category to obtain a clip-level representation. We use a cross-entropy loss on the output probabilities to train our clip classification backbone.

$$\phi_{clip} = MLP_{Category}(\varphi_{c=1}||...||\varphi_{c=C}) \tag{6}$$

Our object-level representation can also easily be combined with video appearance features extracted from a 3D CNN, in our experiments we will be using I3D (Carreira and Zisserman, 2017).

3.3. Temporal Sequence Modeling

Following our clip-based feature extraction, each video is then represented as $v_i = \{\phi_1, ..., \phi_T\}$ with ϕ_t is the feature extracted from the tth clip. Those features can then be concatenated with the I3D features and be fed to Uni-GRU (Cho et al., 2014). This allows us to deal with long-range temporal dependencies and obtain a more robust temporal segmentation for long videos.

4. Experiments and Results

4.1. OR SAR Dataset

We demonstrate the performance of our method on the OR Surgical Action Recognition (SAR) dataset that was first introduced by (Sharghi et al., 2020). This dataset contains 400 full-length videos extracted from 103 surgical procedures. Acquisition of the videos is performed by 4 ToF cameras positioned strategically on two different carts to properly capture the full OR.

Table 1: Results and comparison against baselines for OR surgical activity recognition on complete procedures. mAP (%) is reported across three different splits for all data fractions. We provide the mean average precision averaged across splits.

Surgical Activity Recognition							
Temporal Model	**Backbone**	**Visual Features**	**2 %**	**5 %**	**10 %**	**20 %**	**100 %**
Uni-GRU	I3D	✓	19.7±2.8	39.2±1.9	53.5±1.5	79.5±0.9	90.7±0.6
	ST(OR)^2	×	27.3±2.1	48.8±1.7	58.2±1.9	68.3±1.6	73.6±1.3
	I3D + ST(OR)^2	✓	**29.5±2.3**	**54.2±1.7**	**60.1±1.6**	**82.3±1.4**	**91.8±1.0**

Table 2: Results and comparison against baselines for clip-based surgical action classification. top-1 accuracy (%) is reported.

Surgical Action Classification		
Backbone	**Object-Centric Model**	**Top-1 Accuracy**
I3D	×	87.9±0.9
TimesFormer	×	85.7±0.4
MotionFormer	×	84.5±1.2
I3D	STRG	88.4±1.2
MotionFormer	ORViT	84.1±1.4
×	ST(OR)^2	47.3±2.1
I3D	ST(OR)^2	**89.4±0.8**

Nine activities relative to robotic system utilization are annotated on the entire dataset, and class-specific statistics are provided in (Sharghi et al., 2020). This dataset was later extended with bounding box annotations for persons and objects. Five OR-specific objects are annotated on around 19K frames across 20 full-length videos. Those activities and objects are illustrated in Figure 3.

4.2. Data Efficiency Experiments

For the first experiment, we evaluate our method using an increasing amount of annotated data to assess if our model can learn with fewer activity labels. As shown in Table 1, ST(OR)^2 performs much better than the global feature-based I3D baseline (Carreira and Zisserman, 2017). Up to 10% of labeled data, ST(OR)^2 is better than the I3D without using any visual features. This shows the potential of encoding surgical scenes using our proposed Spatio-Temporal geometric interaction graph for OR surgical activity recognition. We further improve the performance across all percentages of labeled data when we integrate global image-based I3D features with local object-based features. We report the average mean-average precision (mAP) across three different splits, that we sampled randomly, for all data fractions.

Table 3: Results of the object feature ablation study. top-1 accuracy(%) is reported with standard deviation. We cut out separately the Spatial Position Embedding (SPE) and the Category Embedding (CE).

Feature Ablation	
Node Features	**Top-1 Accuracy**
No SPE	33.1 ± 3.1
No CE	44.1 ± 2.2
SPE + CE	**47.3 ± 2.1**

4.3. Clip Classification Experiments

We evaluate our method against both global image-centric and local object-centric approaches. We choose I3D (Carreira and Zisserman, 2017), TimesFormer (Bertasius et al., 2021), and MotionFormer (Patrick et al., 2021) as the global image-centric baselines. We choose STRG (Wang and Gupta, 2018) and ORViT (Herzig et al., 2022) as the local object-centric baselines. The STRG uses global features from I3D, ORViT uses global features from MotionFormer, and our proposed ST(OR)^2 uses global features from I3D. We evaluate the clip-based action classification using Top-1 accuracy. Table 2 shows that baseline approaches without using local object features perform inferior to those using local object features. The proposed ST(OR)^2 overperforms all other baselines.

4.4. Ablation Experiments

We investigate the feature representation of the nodes of our object graph, to show the importance of both spatial position and category embeddings. We run an ablation study by removing spatial position features and category embedding features, respectively. As shown in Table 3, we notice a significant 14.2% and 3.2% drop in performance when not using the spatial position features and category embedding features, respectively. This shows the strong dependence of our approach on the geometric grounding of the scene elements. The category information of the geometrically grounded objects further improves the results.

5. Conclusion

This paper proposes a novel geometrically grounded object-centric approach for OR surgical activity recognition. Our approach exploits the geometric layout of the clinicians and the surgical devices and builds a Spatio-Temporal graph to reason about the underlying surgical activity. We show that our object-centric approach provides superior results against the baseline methods and works particularly well with less labeled supervision. Furthermore, this work only uses a rough geometric representation of objects, i.e., bounding boxes, to induce object awareness in visual representations. In the future, more spatially rich features like human pose estimation of clinicians could be employed to further improve OR surgical activity recognition performance.

Informed consent Data has been collected within an Institutional Review Board (IRB) approved the study and all participants informed consent has been obtained.

Acknowledgments

Acknowledgments withheld.

References

Gedas Bertasius, Heng Wang, and Lorenzo Torresani. Is space-time attention all you need for video understanding? In Marina Meila and Tong Zhang, editors, *Proceedings of the 38th International Conference on Machine Learning, ICML 2021, 18-24 July 2021, Virtual Event*, volume 139 of *Proceedings of Machine Learning Research*, pages 813–824. PMLR, 2021. URL http://proceedings.mlr.press/v139/bertasius21a.html.

Zhaowei Cai and Nuno Vasconcelos. Cascade r-cnn: Delving into high quality object detection. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6154–6162, 2018. doi: 10.1109/CVPR.2018.00644.

João Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4724–4733, 2017. doi: 10.1109/CVPR.2017.502.

Kenneth Catchpole, Colby E Perkins, Catherine Bresee, M. Jonathon Solnik, Benjamin Sherman, John L Fritch, Bruno Gross, Samantha Jagannathan, Niv Hakami-Majd, Raymund M. Avenido, and Jennifer T. Anger. Safety, efficiency and learning curves in robotic surgery: a human factors analysis. *Surgical Endoscopy*, 30:3749–3761, 2015.

Ishani Chakraborty, Ahmed Elgammal, and Randall S. Burd. Video based activity recognition in trauma resuscitation. In *2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*, pages 1–8, 2013.

Kyunghyun Cho, Bart van Merrienboer, Çaglar Gülçehre, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using RNN encoder-decoder for statistical machine translation. *EMNLP*, abs/1406.1078, 2014. URL http://arxiv.org/abs/1406.1078.

Tobias Czempiel, Magdalini Paschali, Matthias Keicher, Walter Simson, Hubertus Feussner, Seong Tae Kim, and Nassir Navab. TeCNO: Surgical phase recognition with multi-stage temporal convolutional networks. In *Medical Image Computing and Computer Assisted Intervention – MICCAI 2020*, pages 343–352. Springer International Publishing, 2020. doi: 10.1007/978-3-030-59716-0_33. URL https://doi.org/10.1007%2F978-3-030-59716-0_33.

Christoph Feichtenhofer. X3d: Expanding architectures for efficient video recognition. *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 200–210, 2020.

Christoph Feichtenhofer, Haoqi Fan, Jitendra Malik, and Kaiming He. Slowfast networks for video recognition. *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 6201–6210, 2018.

Hassan Al Hajj, Mathieu Lamard, Pierre-Henri Conze, Béatrice Cochener, and Gwenolé Quellec. Monitoring tool usage in surgery videos using boosted convolutional and recurrent neural networks. *MedIA*, 47:203–218, July 2018.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *CoRR*, abs/1512.03385, 2015. URL http://arxiv.org/abs/1512.03385.

Zhuohong He, Ali Mottaghi, Aidean Sharghi, Muhammad Abdullah Jamal, and Omid Mohareri. An empirical study on activity recognition in long surgical videos. In Antonio Parziale, Monica Agrawal, Shalmali Joshi, Irene Y. Chen, Shengpu Tang, Luis Oala, and Adarsh Subbaswamy, editors, *Proceedings of the 2nd Machine Learning for Health symposium*, volume 193 of *Proceedings of Machine Learning Research*, pages 356–372. PMLR, 28 Nov 2022. URL https://proceedings.mlr.press/v193/he22a.html.

Roei Herzig, Elad Ben-Avraham, Karttikeya Mangalam, Amir Bar, Gal Chechik, Anna Rohrbach, Trevor Darrell, and Amir Globerson. Object-region video transformers. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2022, New Orleans, LA, USA, June 18-24, 2022*, pages 3138–3149. IEEE, 2022. doi: 10.1109/CVPR52688.2022.00315. URL https://doi.org/10.1109/CVPR52688.2022.00315.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9:1735–80, 12 1997. doi: 10.1162/neco.1997.9.8.1735.

Thibaut Issenhuth, Vinkle Kumar Srivastav, Afshin Gangi, and Nicolas Padoy. Face detection in the operating room: comparison of state-of-the-art methods and a self-supervised approach. *IJCARS*, 2019.

Muhammad Abdullah Jamal and Omid Mohareri. Multi-modal unsupervised pre-training for surgical operating room workflow analysis. In *Medical Image Computing and Computer Assisted Intervention – MICCAI 2022*, 2022.

Abdolrahim Kadkhodamohammadi, Nachappa Sivanesan Uthraraj, Petros Giataganas, Gauthier Gras, Karen Kerr, Imanol Luengo, Sam Oussedik, and Danail Stoyanov. Towards video-based surgical workflow understanding in open orthopaedic surgery. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, 9 (3):286–293, 2021.

Falisha Kanji, Tara Cohen, Myrtede Alfred, Ashley Caron, Samuel Lawton, Stephen Savage, Daniel Shouhed, Jennifer T Anger, and Ken Catchpole. Room size influences flow in robotic-assisted surgery, Jul 2021. URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8345669/.

Colin Lea, René Vidal, Austin Reiter, and Gregory D. Hager. Temporal convolutional networks: A unified approach to action segmentation. In Gang Hua and Hervé Jégou, editors, *ECCV 2016 Workshops*, pages 47–54, Cham, 2016. Springer International Publishing. ISBN 978-3-319-49409-8.

Zhaoshuo Li, Amirreza Shaban, Jean-Gabriel Simard, Dinesh Rabindran, Simon P. DiMaio, and Omid Mohareri. A robotic 3d perception system for operating room environment awareness. *IPCAI*, 2020.

Zhuang Liu, Hanzi Mao, Chao-Yuan Wu, Christoph Feichtenhofer, Trevor Darrell, and Saining Xie. A convnet for the 2020s. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 11976–11986, June 2022.

Zelun Luo, Jun-Ting Hsieh, Niranjan Balachandar, Serena Yeung, Guido Pusiol, Jay S. Luxenberg, Grace Li, Li-Jia Li, Arnold Milstein, and Li Fei-Fei. Vision-based descriptive analytics of seniors ' daily activities for long-term health monitoring. 2018.

Lena Maier-Hein, Matthias Eisenmann, Duygu Sarikaya, Keno März, Toby Collins, Anand Malpani, Johannes Fallert, Hubertus Feussner, Stamatia Giannarou, Pietro Mascagni, et al. Surgical data science–from concepts toward clinical translation. *Medical image analysis*, 76:102306, 2022.

Pietro Mascagni and Nicolas Padoy. Or black box and surgical control tower: recording and streaming data and analytics to improve surgical care. *Journal of Visceral Surgery*, 158(3):S18–S25, 2021.

Joanna Materzynska, Tete Xiao, Roei Herzig, Huijuan Xu, Xiaolong Wang, and Trevor Darrell. Something-else: Compositional action recognition with spatial-temporal interaction networks. *CVPR*, abs/1912.09930, 2019. URL http://arxiv.org/abs/1912.09930.

Aditya Murali, Deepak Alapatt, Pietro Mascagni, Armine Vardazaryan, Alain Garcia, Nariaki Okamoto, Didier Mutter, and Nicolas Padoy. Latent graph representations for critical view of safety assessment, 2022. URL https://arxiv.org/abs/2212.04155.

Ege Özsoy, Evin Pinar Örnek, Ulrich Eck, Tobias Czempiel, Federico Tombari, and Nassir Navab. 4d-or: Semantic scene graphs for OR domain modeling. In Linwei Wang, Qi Dou, P. Thomas Fletcher, Stefanie Speidel, and Shuo Li, editors, *Medical Image Computing and Computer Assisted Intervention - MICCAI 2022 - 25th International Conference, Singapore, September 18-22, 2022, Proceedings, Part VII*, volume 13437 of *Lecture Notes in Computer Science*, pages 475–485. Springer, 2022. doi: 10.1007/978-3-031-16449-1_45. URL https://doi.org/10.1007/978-3-031-16449-1_45.

Nicolas Padoy. Machine and deep learning for workflow recognition during surgery. *Minimally Invasive Therapy & Allied Technologies*, 28(2):82–90, 2019.

Mandela Patrick, Dylan Campbell, Yuki M. Asano, Ishan Misra, Florian Metze, Christoph Feichtenhofer, Andrea Vedaldi, and João F. Henriques. Keeping your eye on the ball: Trajectory attention in video transformers. In Marc'Aurelio Ranzato, Alina Beygelzimer, Yann N. Dauphin, Percy Liang, and Jennifer Wortman Vaughan, editors, *Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS 2021, December 6-14, 2021, virtual*, pages 12493–12506, 2021. URL https://proceedings.neurips.cc/paper/2021/hash/67f7fb873eaf29526a11a9b7ac33bfac-Abstract.html.

Nicolas Loy Rodas, Fernando Barrera, and Nicolas Padoy. See it with your own eyes: Markerless mobile augmented reality for radiation awareness in the hybrid room. *IEEE Transactions on Biomedical Engineering*, 64(2):429–440, 2016.

Lauren Schiff, Ziv Tsafrir, Joe Aoun, Andrew R. Taylor, Evan Theoharis, and David Eisenstein. Quality of communication in robotic surgery and surgical outcomes. *JSLS : Journal of the Society of Laparoendoscopic Surgeons*, 20, 2016.

Adam Schmidt, Aidean Sharghi, Helene Haugerud, Daniel Oh, and Omid Mohareri. Multi-view surgical video action detection via mixed global view attention. In *MICCAI*, 2021.

Aidean Sharghi, Helene Haugerud, Daniel Oh, and Omid Mohareri. Automatic operating room surgical activity recognition for robot-assisted surgery. In *MICCAI*, 2020.

Dimick JB. Sheetz KH, Claflin J. Trends in the adoption of robotic surgery for common surgical procedures. *JAMA Network Open*, 2020.

Vinkle Srivastav, Afshin Gangi, and Nicolas Padoy. Self-supervision on unlabelled or data for multi-person 2d/3d human pose estimation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 761–771. Springer, 2020.

Vinkle Kumar Srivastav, Thibaut Issenhuth, Abdolrahim Kadkhodamohammadi, Michel de Mathelin, Afshin Gangi, and Nicolas Padoy. Mvor: A multi-view rgb-d operating room dataset for 2d and 3d human pose estimation. *ArXiv*, abs/1808.08180, 2018.

Vinkle Kumar Srivastav, Afshin Gangi, and Nicolas Padoy. Human pose estimation on privacy-preserving low-resolution depth images. *MICCAI*, abs/2007.08340, 2019.

Joshua B. Tenenbaum, Charles Kemp, Thomas L. Griffiths, and Noah D. Goodman. How to grow a mind: Statistics, structure, and abstraction. *Science*, 331:1279 – 1285, 2011.

Andru P. Twinanda, Sherif Shehata, Didier Mutter, Jacques Marescaux, Michel de Mathelin, and Nicolas Padoy. EndoNet: A deep architecture for recognition tasks on laparoscopic videos. *IEEE TMI*, 36(1):86–97, January 2017a.

Andru Putra Twinanda, Pramita Winata, Afshin Gangi, Michel De, Mathelin, and Nicolas Padoy. Multi-stream deep architecture for surgical phase recognition on multi-view rgbd videos. 2017b.

Tom Vercauteren, Mathias Unberath, Nicolas Padoy, and Nassir Navab. Cai4cai: the rise of contextual artificial intelligence in computer-assisted interventions. *Proceedings of the IEEE*, 108(1):198–214, 2019.

Xiaolong Wang and Abhinav Gupta. Videos as space-time region graphs. *ECCV*, abs/1806.01810, 2018. URL http://arxiv.org/abs/1806.01810.

Chuhan Zhang, Ankush Gupta, and Andrew Zisserman. Is an object-centric video representation beneficial for transfer? *ACCV*, abs/2207.10075, 2022. doi: 10.48550/arXiv.2207.10075. URL https://doi.org/10.48550/arXiv.2207.10075.

Yanyi Zhang, Ivan Marsic, and Randall S Burd. Real-time medical phase recognition using long-term video understanding and progress gate method. *Medical Image Analysis*, 74: 102224, 2021.

Table 4: Class-specific performance for object detection class-specific. mAP at IoU:0.5:0.95 (%) is reported on the testing set for our detector.

Object Detection Performance						
Method	**Human**	**Table**	**Gurney**	**PSC**	**OR Table**	**VSC**
Cascade MaskRCNN	79.3	65.4	57.4	70.2	46.4	69.7

Appendix A. Implementation Details

In our experiments, we set the number of bounding boxes used in each frame to 15. This number was chosen by taking the max number of objects per video across all videos in the training set. The dimension of the spatial position embedding and the category embedding is chosen as 1024, We train all our backbones for 50 epochs using stochastic gradient descent as our optimizer. We use a cosine policy learning rate with a warmup start learning rate of 0.01, a momentum equal to 0.9, and a weight decay of $1e-6$. Our models are trained on 4 Nvidia V-100 GPUs, using a batch size of 32 clips.

Appendix B. Object Detection Specifics

The main limitation of our method is the weak object detector as we only rely on bounding box information to recognize clip actions. We provide per-class performance for our object detector in Table 4. We also report in the same table the performance of the human detector which is significantly superior.

Appendix C. Class-specific performance for Action Recognition

We compare the performance of our approach without any visual features for the nine different OR surgical activities. As is shown in the confusion matrix provided in Figure 4, our approach tends to underperform in recognizing the Docking, Undocking, and Surgery phases. Those three phases are consecutive and only involve fine-grained movement of the clinician's hands to install or uninstall the instruments on the PSC. The lack of overall movement from the surgical equipment does not provide enough information to our model to correctly classify those actions. On the other hand, actions that are closely associated with the movement of surgical devices like the Roll-Up and Roll-Back of the daVinci robot give the best performance with a compelling 69% Top-1 accuracy.

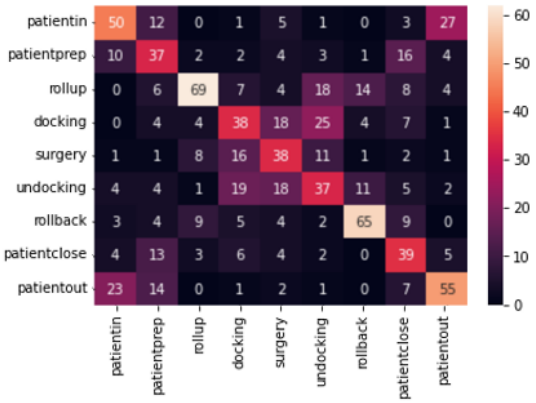

Figure 4: Confusion Matrix for OR Surgical Action Recognition.