7-DoF laparoscopic peg transfer dataset for surgical skill assessment

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Abstract
This work introduces **LASK** (**LA**paroscopic **S**kill & **K**inematics), a peg-transfer surgical dataset featuring synchronised HD video and 7-DoF (seven-degree-of-freedom) ground-truth kinematics for two surgical graspers. The dataset comprises 114 trials (~3 hours total) from 38 low-, 41 medium- and 35 high-skill expert surgeons, providing 324,101 frames with time-aligned kinematics for both tool and tooltips; 3,725 frames are annotated with bounding boxes, including a complete 2,680-frame validation sequence. LASK distinctively captures two instruments throughout with wider fields of view than typical *in-vivo* data, includes surgeon-specific metadata (handedness & experience), and reflects typical box-trainer imaging conditions. These features support robust benchmarking of multi-class detection, tracking, pose estimation, skill

assessment and classification algorithms. Once publicly released, LASK aims to improve laparoscopic training by fostering data-driven training tools.

Introduction

Minimally Invasive Surgery (MIS), particularly laparoscopy, offers significant patient benefits but faces adoption challenges globally, especially in resource-constrained environments (RCEs) due to surgeon skill gaps and equipment costs (Jaffray, 2005; Meara et al., 2015). Effective training is paramount, and computer-assisted systems powered by AI can provide objective skill assessment and democratise access to quality surgical education (Bodenstedt et al., 2018). However, developing such AI tools is hampered by a scarcity of publicly available, well-annotated datasets that combine synchronised video with detailed instrument kinematics, especially for non-*in-vivo* training tasks relevant to fundamental skill acquisition and RCE contexts (Ali et al., 2023; Maier-Hein et al., 2022). Existing datasets are often *in-vivo* with limited kinematics, or robotic-centric, which, while rich in data, may not fully align with the needs of conventional laparoscopic training or low-cost setups (Rodrigues et al., 2022). This paper introduces LASK, a novel dataset designed to address these limitations.

Related Work and Motivation

Most publicly available laparoscopic datasets are *in-vivo* and image-only, e.g. the various Cholec and successive EndoVis challenge datasets, providing phase labels, tool presence or 2D boxes but *no* instrument pose ground truth (Ali et al., 2023; Bouget et al., 2017; EndoVis Sub-Challenge, 2015 Hong et al., 2020; Nwoye et al., 2023). The few datasets which do frequently include accurate, comprehensive kinematics are robotic: JIGSAWS and ROSMA supply time-synchronised 6-DoF tip pose and jaw angle, yet captured on costly da Vinci platforms and do not represent non-robotic training realities or RCE constraints (Gao et al., 2015; Rivas-Blanco et al., 2023). Training task datasets remain scarce and limited: PETRAW is entirely simulated, not representing realistic visual conditions, SimSurgSkill logs coarse VR controller data, and the WMU box-trainer provides only sparse 2D annotations without kinematics (Fathabadi & Grantner, 2022; Huaulmé et al., 2023). Consequently, *no* open resource delivers continuous, ground-truth position and orientation, jaw angles *plus* surgeon-level skill metadata throughout a realistic non-robotic training task.

The LASK Dataset

The LASK (**LA**paroscopic **S**kill & **K**inematics) dataset (Figure 1) was collected throughout the 7th and 8th Urology Boot Camps in Leeds, UK (in 2023 and 2024) and at the annual British Association of Paediatric Endoscopic Surgeons (BAPES) 2024 congress, using a standard laparoscopic box trainer. Surgeons performed the peg transfer task, a fundamental laparoscopic training exercise[1], in which the task is to move all six blocks from the left side of the board to the right side, switching the block between the left and right hands, repeating again once all blocks are on the right side.

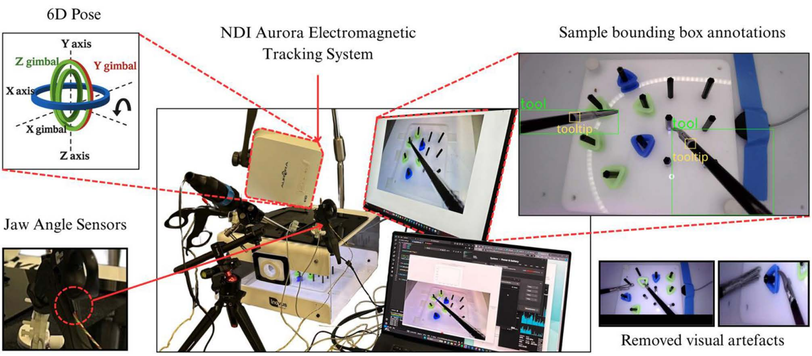

FIGURE 1
Overview of the LASK data collection setup and sample annotated video frame.

[1] Widely used for training, including in the European Basic Laparoscopic Urological Skills (E-BLUS) and American Fundamentals of Laparoscopic Surgery (FLS) exams.

Data acquisition and participants

We recorded 114 trials, each from distinct participants: 38 low-skill novices (early-trainees, <20 lifetime cases), 41 medium-skill (more experienced trainees, 20-100 cases) and 35 high-skill expert (consultant, >200 cases) surgeons (84 adult and 30 paediatric). Demographic data reveal a median of 50 lifetime laparoscopic cases (IQR 10-200), with 103 right-handed, 5 left-handed, and 6 mixed-handed individuals. Notably, 9 surgeons appeared to have transitioned from laparoscopy to robotics (0 laparoscopic cases within the last 12 months despite >100 lifetime).

Dataset annotations and quality

Synchronised multimodal data was captured:

- Video: High-definition (1280x720, 30FPS, H.264) monocular video from a USB camera, resulting in ~3 hours of footage (324,101 frames total, ~2 minutes per task). The setup intentionally reflected lighting variability and imaging typical of lower-cost training environments.

- Kinematics (7-DoF): NDI Aurora electromagnetic trackers (Hummel et al., 2005) provided 7-DoF data: 3D Cartesian position [x, y, z] for tools and camera (calibrated using a chessboard (OpenCV, 2025)), 3D quaternion orientation [q_w, q_x, q_y, q_z], and grasper jaw opening angle for both left and right surgical instruments (derived from the voltage level using magnetic sensor markers on the grasper handles).

- Bounding Boxes: 3,725 frames contain COCO-style bounding boxes for tool shafts and tips. These comprise sparsely labelled frames (every 100th frame) from 23 videos (with 1,045 sparsely labelled frames, reduced to 864 clean annotation files after quality control) and one fully annotated video for training/validation (2,680 consecutive frames).

- Issues: There are minor issues, such as occasional overexposure, frame cuts, or camera overheating artefacts (noted and managed during quality control). Throughout the various collection events, cameras and subsequent calibration changes occurred, although tools and tasks remained the same.

Dataset Utility and Potential Research
LASK is the first laparoscopic peg-transfer dataset with synchronised video and comprehensive kinematic data, tailored for skill assessment research. In future work, we plan to release the dataset with segmentation masks publicly, additional annotated validation videos and attained baseline benchmarks. The dataset is well-suited for:

- Multi-tool detection (preliminary benchmarks with state-of-the-art YOLO models show >95% accuracy) and tracking in training environments.

- 3D tool pose estimation, including jaw opening, from monocular video.

- Objective surgical skill assessment and classification (Jones et al., 2018).

- Investigating the performance impact of handedness and experience.

We hope this offers an essential resource to the computer vision and surgical data science communities, aiming to foster robust, data-driven training tools and democratise laparoscopic education worldwide.

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