Proceedings of the Joint Austrian Computer Vision and Robotics Workshop 2020 DOI: 10.3217/978-3-85125-752-6-13

Automated Log Ordering through Robotic Grasper

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Abstract. *This work focuses on retrofitting a crane model in the wood industry for automated log grasping. AI inspired vision based approaches are used to categorize and segment the logs and their geometry to subsequently define optimal grasping poses. Retrofittable sensors and robust control strategies for cost efficient upgrading of existing manually operated cranes towards autonomous systems are developed.*

1. Introduction

Classical production lines and handling processes for raw materials often have a long history and incorporate a large amount of experience based knowledge for process optimization and handling routines. Nowadays, these processes seem to be stuck in a local minima in terms of efficiency and performance due to human factors. With the available degree of automation, robustness of AI based perception and decision making, and novel sensor technology, a re-thinking of these well established processes can take place. Instead of a radical approach to replace existing infrastructure, this work leverages currently installed machines in the wood sector and enables them to work autonomously through retro-fitting of sensors, autonomy, and AI based scene understanding. The project has a strong focus on bringing advanced methods in the corresponding research fields to practice. Hence, a model log crane was built as a 1:5 scaled down copy of a real log crane (Fig. 1).

* The research leading to these results has received funding from BMVIT under grant n. 864807 (AutoLOG)

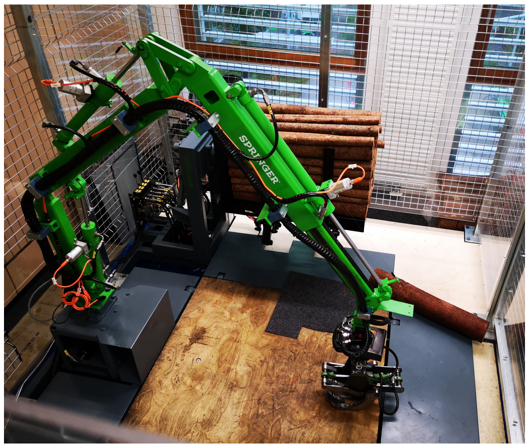

Figure 1. Crane model in 1:5 scaled version of a real crane used in the wood sector. The hydraulics are specifically designed to match this scale. Manual control is identical to the real versions.

2. Model and Retrofittable Sensor Design

The 1:5 scaled crane model has been designed and manufactured from scratch to match the properties of the real counterparts. This includes hydraulic actuators, end-effector with two free joints and an actuated revolute joint with unconstrained 360° actuation, and backlash. For tests and evaluation, we installed wire-rope sensors on the hydraulic pistons to measure their current position. Novel capacitive and inductive sensors have been designed and implemented as described in Section 2.1 to measure the current absolute angles and to provide feedback on the grasping quality. Apart of the crane itself, the overall system (Fig. 2) also contains a log storage box with automated emptying mechanism. Emptying the box is done by asynchronously opening the box such that the model logs spread randomly on the floor. The floor area designed as log picking area can be shielded during a box emptying process to prevent the logs from spreading too wide in the area. With the project goal of the crane being able to autonomously store the logs in the box, this automated emptying process enables an endless cycle for automated training refining the AI based procedures without supervision.

The crane is controlled at a high level by an external PC which is connected via Ethernet to a HAWE-ESX control unit. The ESX controls the hydraulic pistons and sends the signals of the wire-rope and custom angular sensors via Ethernet back to the host PC. The PC also receives data from two cameras mounted on the fix and movable part of the crane as well as from five IMUs mounted on each of the crane joints. These sensors will serve for automated model creation as we assume to not have CAD drawings of every crane in a retrofitting process. The overall connectivity schematic is shown in Fig. 3.

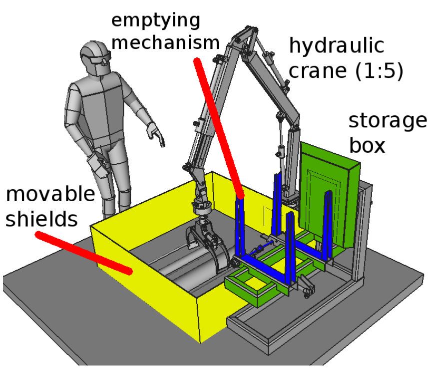

Figure 2. Crane model system with automated elements for continuous learning without human intervention.

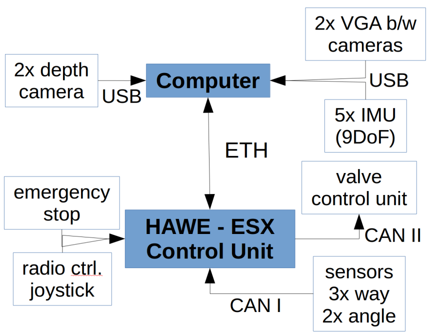

Figure 3. Overview on the connectivity of the model crane, the sensors, and the external PC.

2.1. Retrofittable Sensors

Automating machinery in the wood sector is challenging since not only the sensors that enable autonomy need to be equipped ideally without disassembling the machine, they also need to be autarkic in terms of energy, and withstand very harsh environments. Thus, robust magnetic angular position sensors following [1] suitable for retrofitting and wireless operation have been integrated on the crane model. They can easily be adapted for different joint geometries. The basic architecture is shown in Fig. 4 together with the lab setup (currently with wired CAN). In addition, capacitive sensors

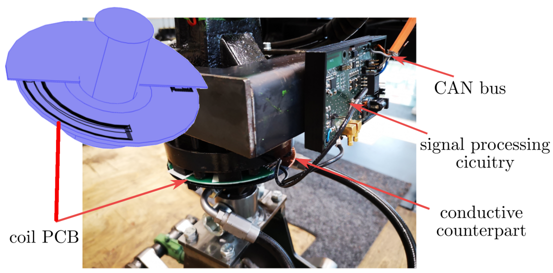

Figure 4. The experimental sensor and CAD coil geometry on the rotary joint of the end-effector: The coil PCB and signal processing circuitry is mounted to the non-rotating head whereas the conductive plate is mounted on the rotating shaft. The conductive counterpart consists of a 3D printed holder and wrapped copper foil.

following [2] are integrated in the end-effector to augment the machinery with a sense for log grasping quality (Fig. 5). The crane and sensors are simulated

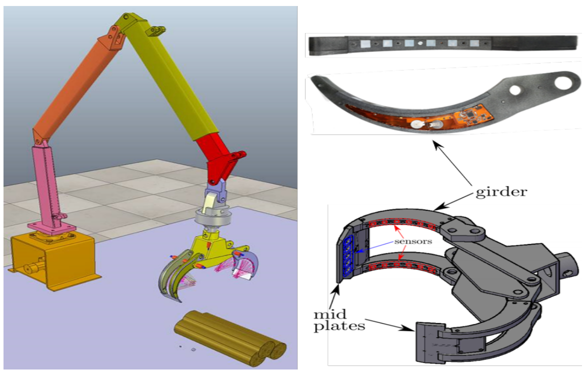

Figure 5. Left: V-REP model. Bottom right: gripper design. Top right: photograph of the gripper prototype including the sensor elements wireless electronics.

in V-REP. There, the communication and control are tested using V-REP/ROS and V-REP/Python bridge. The simulation also serves as an environment for AI training of the crane controls and for optimizations on sensor placement following [3]. A video of the simulation framework can be found in [4]

3. Control and State Estimation

The manipulator as a forest crane is vastly different compared to a standard industrial robot: the rather unconventional design requires detailed geometrical knowledge to derive the kinematic model. Also, the hydraulic driving system suffers from heavy vibrations, backlashes and jerks which require detailed dynamic parameters for proper modelling. To capture the complex relationships on existing machines where CAD and dynamic models are rarely available, we use machine learning techniques for the prediction of kinematics and dynamics parameters. Additional inertial and visual sensors further help to re-fine the overall state estimation including the adaptive estimation of the dynamic parameters defining the sway-motion of the two free joints on the end-effector. This adaptive estimation of the kinematic and dynamic parameters allows a simplified manipulator model for adaptive control schemes when picking and placing logs with sway motion.

3.1. Automated Grasping Point Prediction

To find the optimal points for the gripper to grasp a log (or logs), it is necessary to recognize graspable objects in the surrounding area of the robotic manipulator and calculate possible candidates. A candidate is defined as a point/area of the log which can successfully be grasped by the gripper. A ZED camera is used for image acquisition and consists of a stereo camera system capturing high resolution RGB-D images from the scene. Core component of the prediction method is a deep learning approach using a Convolutional Neural Network to predict grasping candidates in 2D image space, similar to [5]. The depth information is used for: 1) Automatic annotation of training data for a deep neural network by leveraging sequential depth data. This method is a step towards continuous learning making it easily possible to generate new ground truth training data during real time system application. 2) Calculation of the final 3D position of the grasping point from the previously predicted 2D grasping candidate. Fig. 6 shows a sample scenario with some logs remaining in the picking area and marked grasping locations by the AI method.

3.2. Conclusion and Next Steps

We proposed a mechanical setup for training a crane model of the wood industry for automated log grasping. The setup allows automated operation such that continuous learning without human intervention can be possible. Retrofittable sensors allow additional sensing capability in order to autonomously control the grasping procedure and to verify correct picking of the desired logs. The current results show that while the alignment of the desired gripper positions to grasp a log is correctly predicted by the AI, not all suggested locations are ideal in view of the center of gravity. Next steps will include the feedback of the capacitive sensors to correct the AI decision in an automated learning procedure.

Figure 6. Model logs in the picking area of the 1:5 scaled model crane with marked grasping positions by our AI based method. Red marks the desired locations of the two grippers in the end-effector of the crane.

References

[1] H. Gietler, C. Stetco, and H. Zangl, "Scalable retrofit angular position sensor system," in *IEEE International Conference on Instrumentation and Measurement*, Dubrovnik, May 2020.

[2] L. Faller, C. Stetco, and H. Zangl, "Design of a novel gripper system with 3d- and inkjet-printed multimodal sensors for automated grasping of a forestry robot," in *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Nov 2019, pp. 5620–5627.

[3] T. Mitterer and H. Zangl, "Beyond pure sensing: Ieee 21450 in digitalization of the development cycle of smart transducers," *IEEE Instrumentation & Measurement Magazine*, April 2020.

[4] Sensors for automated grasping of forestry robots. www.youtube.com/watch?v=B1S46LqfG48.

[5] F.-J. Chu, R. Xu, and P. A. Vela, "Real-world multiobject, multigrasp detection," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 3355–3362, 2018.