Proceedings of the

Challenges in
Automated Food Processing

Workshop at

European Robotics Forum, 2021

Hosted in association with the

RoBUTCHER project:
A Robust, Flexible and Scalable Cognitive Robotics Platform
The workshop was hosted by the RoBUTCHER Project. This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 871631.

Read more about the RoBUTCHER Project at: https://www.robutcher.eu/
Foreword

by Dr. Alex Mason

The application of machines in the agri-food sector has always been fundamental. With time, those machines have developed in complexity, but still the sector is left requiring more to keep up with the challenges and demands of the 21st century.

The agri-food sector is perhaps the most demanding manufacturing sector due to the variable nature of the raw material and relatively small margins. This has resulted in many tasks remaining manual, using human operators to cut, sort and process material in highpace environments. Increasingly the sector finds it difficult to maintain work forces, with shrinking labour pools widely reported, and exacerbated by the Covid-19 pandemic. Furthermore, poor access to automation creates huge divides between the large and small-scale producers, and overall reduces the yield, efficiency and security of food value chains.

This workshop session, as part of the European Robotics Forums 2021, aims to present some of the latest trends and developments related to food processing and robotics, and to discuss the road map for future enhancements to these fields.
CALL FOR POSTERS

European Robotics Forum (ERF 2021)

Workshop on: Challenges in Automated Food Processing

April 15, 2021

RoBUTCHER

https://www.eu-robotics.net/robotics_forum

Workshop agenda

• **Keynote talk**: Prof. Alex Mason (NMBU), Standardized red meat processing in the 21st century
• **E-Poster teaser presentations**
  3 min for each accepted abstract
• **Roundtable discussion**: Identifying the key challenges in standardized food processing industry solutions (moderated by Dr. Steven Ross, NMBU)

Workshop information

• Within the frames of ERF 2021, the workshop will be held on **day 3, April 15, 14:05 – 15:25**
• Registration link: [https://www.eu-robotics.net/robotics_forum/registration/index.html](https://www.eu-robotics.net/robotics_forum/registration/index.html)

Organizers:

• T. Haidegger & K. Takács, Óbuda University, University Research and Innovation Center; [http://irob.uni-obuda.hu/](http://irob.uni-obuda.hu/)
• A. Mason & S. Ross, Norwegian University of Life Sciences [https://www.nmbu.no/](https://www.nmbu.no/)
• RoBUTCHER project: A Robust, Flexible and Scalable Cognitive Robotics Platform [https://robutcher.eu/](https://robutcher.eu/)

Extended abstract submission:

• Max. 2 pages, PDF abstracts (double column IEEE format)
• Send to [robutcher@irob.uni-obuda.hu](mailto:robutcher@irob.uni-obuda.hu)
• Deadline: 24:00, April 11, 2021 CET
• Notification: April 12, 2021

Contributions are invited fitting the topic of the workshop in the given format, from the entire community. Selected abstracts will be invited to give an e-poster presentation (3 min), and will be featured on the event’s website. Best poster award will be presented.

Topical Focus

Robotics in the food-industry deems to be necessary to keep up with the challenges and demands of the 21st century. The goal of this workshop is to present the latest trends and developments related to food & food processing robotics, and to discuss the roadmap for future enhancements to these fields. Research and expert statements abstracts, delivered as e-poster presentations are sought in the overall topical area of food and agricultural robotics, including but not limited to:

- Mechatronics for agro-food
- Meat sector automation solutions
- Poultry production and automation
- Robotics for food processing

In the keynote, the RoBUTCHER H2020 project will be presented, which aims to build the first completely automated cell-based slaughterhouse.
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Computer vision for Robotic Butcher

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Abstract—To support the autonomous Meat Factory Cell in which two robots will perform the gripping and cutting of the pig carcass, this work presents the application of the deep learning to locate gripping points on the carcass limbs and prediction of 3D cutting trajectories using U-Net-based approach with ResNet backbones.

Keywords—deep learning, computer vision, gripping points location, trajectory prediction

I. INTRODUCTION

The fixation with line production in the meat sector has meant that automation solutions, particularly for slaughter, cutting or deboning processes, require big investments and are only accessible to the very largest of meat producers. The RoBUTCHER [1] concept aims for smaller producers to be able to automate their production more cost effectively than is possible today.

The RoBUTCHER concept enables an autonomous meat factory cell (MFC). In the RoBUTCHER the robotic system will be able to understand and plan cutting trajectories based on the carcass that is presented. To achieve this it will use a combination of detailed computed tomography (CT) data, real-time 3D imagery and human-expert cutting data for neural network training toward cutting trajectory planning.

This work presents the first results of the application of several deep learning techniques to processing the combined RGB and 3D data from multiple cameras depicting the pig carcass to obtain the location of gripping points on the pig limbs and cutting trajectories.

II. DEEP LEARNING BASED COMPUTER VISION SYSTEM FOR ROBOTIC BUTCHER CONTROL

A. System architecture

The computer vision system is proposed which contains of two modules:

1. Gripping point estimation module to provide the robot the locations of the gripping points on the pig limbs to gasp and move according to the need of MFC operation.

2. Cutting pathway module to provide the coordinates of the cutting trajectories and other required information to implement the cuts.

The cutting pathway module contains three submodules: Surface trajectory segmentation submodule, 3D pig mapping module and morphing using PigAtlas, and Trajectory fusion module.

B. Gripping points location

To locate the gripping points on the pig’s limbs a U-Net-based approach with different backbones (ResNet34, ResNet101) is adopted [2-4]. To predict the key points one can use RGB images, as well as RGBD images (RGB + Depth channel) without massive changes in neural network architecture. The outcome of the algorithm for key point location prediction is a heatmap on which the model provides the most likely positions of key points and gripping points and the normal vectors to these points (Fig. 1) to send the orientation data to the robot.

C. Pointclouds matching

One important piece of the RoBUTCHER project is segmentation of the point clouds which are provided by the RGBD cameras. In contrast to regular image segmentation, NVIDIA provides a powerful library to perform any kind of 3D data processing: NVIDIA-Kaolin. Based on this library and DGX station which includes 4 V100- GPUs we were able to train a segmentation model which includes millions of points. We used PointNet++ architecture with NVIDIA-Kaolin framework to manage all the training experiments [5-7]. We also used NVIDIA-Kaolin renderers to visualize segmentation results (Fig. 2).
D. Cutting trajectory prediction and merging

Cutting pathway module was approached as a segmentation task. Model needs to predict six types of cuts, which are also divided into external and internal cuts. U-Net-like architecture with a ResNet-34 backbone was implemented as a solution. To deal with data imbalance we also add classification head, which predicts cuts priority for input images. Weighted sum of BCE losses for segmentation and classification head was used. Model was trained on DGX station which includes 4 V100 GPUs using Apex to increase speed of training with 16-bit precision.

As a result, the model returns a segmentation mask which combined with depth channel transforms to a point cloud. On the post-processing step an unordered set of points skeletonized to the path plan provided to the robot (Figure 3).

III. RESULTS AND CONCLUSIONS

In the result, RoBUTCHER computer vision system comprises many tasks of RGBD-camera data processing using deep learning, such as point clouds segmentation and key points location. The combination of the custom and state of the art deep learning approaches supported by utilization of DGX station and Apex library allowed to demonstrate the first promising results in providing the gripping points location and cutting trajectories on the pig carcass.

REFERENCES

COMPUTER VISION FOR ROBOT BUTCHER

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This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 871631.

The architecture of RoBUTCHER computer vision system

The computer vision system (Figure 3) contains two modules:

- Gripping points estimation module to provide the robot the locations of the gripping points on the pig’s limbs to grasp and move according to the need of MFC operation,
- Cutting pathway module to provide the coordinates of the cutting trajectories and other required information to implement the cuts.

The Cutting pathway module contains three submodules:

- Surface trajectory segmentation submodule
- 3D pig mapping and morphing submodule based on PigAtlas
- Trajectory fusion submodule

Two submodules are working independently on demand. The Vision SDK provides the Computer Vision system with the data from six RGBD cameras placed on the frame around the pig carcass and based on these data the trajectory of the cutting tool is calculated. Every view from the camera is being processed independently and post-processed with 3D fusion.

Gripping points location

To locate the gripping points on the pig’s limbs a U-Net-based approach with different backbones (ResNet54, RethNet56) is adopted. To predict the key points one can use RGB images, as well as RGBD images (RGB + Depth channel) without massive changes in neural network architecture (Fig. 2). The outcome of the algorithm for keypoint location prediction is a heatmap (Fig. 3) on which the model provides the most likely positions of keypoints and gripping points (Fig. 4) and the normal vectors to these points (Fig. 5) to send the orientation data to the robot.

Introduction

The fixation with live production in the meat sector has meant that automation processes, requiring big investments and are only accessible to the very largest meat producers. The RoBUTCHER concept aims for smaller producers to be able to automate their production more cost-effectively than is possible today.

The RoBUTCHER concept enables an autonomous meat factory cell (MFC). In the RoBUTCHER the robotic system will be able to understand and plan cutting trajectories based on the carcass that is presented. To achieve this it will use a combination of detailed computed tomography (CT) data, real-time 3D imagery and human-expert cutting data for neural network training towards cutting trajectory planning.

The main emphasis of the project is research into AI and cognitive systems, which will provide the necessary understanding for the MFC to interact with the carcasses through physical tasks like cutting, grasping and lifting. This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 871631.

Pointclouds matching

One important piece of the RoBUTCHER project is segmentation of the point clouds which are provided by the RGBD camera. In contrast to regular image segmentation, NVIDIA provides a powerful library to perform any kind of 3D data processing - NVIDIA-Kaolin. Based on this library and DGX station which includes 4 V100 GPUs we were able to train a segmentation model which includes millions of points. We used PointNet++ architecture with NVIDIA-Kaolin framework to manage all the training experiments. We also used NVIDIA-Kaolin renders to visualize segmentation results (Fig. 4).

Cutting trajectory prediction and merging

Cutting pathway module was approached as a segmentation task. Model needs to predict six types of cuts (Fig. 7), which are also divided into external and internal cuts. U-Net-like architecture with a ResNet-34 backbone was implemented as a solution. To deal with data imbalance we also add classification head, which predicts cuts priority for input images. Weighted sum of BCE losses for segmentation and classification head was used. Model was trained on DGX station which includes 4 V100 GPUs using Apex to increase speed of training with 16-bit precision (see Table 2).

Table 1

<table>
<thead>
<tr>
<th>U-Net-based approach with different backbones</th>
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As a result, the model returns a segmentation mask which combined with depth channel transforms to a point cloud. On the post-processing step an unordered set of points skeletonized to the path plan provided to the robot.

Conclusions

RoBUTCHER computer vision system comprises many tasks of RGBD camera data processing using deep learning, such as point clouds segmentation and keypoint location. The combination of the current state of the art of deep learning approaches supported by utilization of DGX station and Apex library allowed to demonstrate the first promising results in providing the gripping points location and cutting trajectories on the pig carcass.

References


Vision SDK

Computer Vision System

Figure 1: Example of visualizations of RGB image and depth image

Figure 2: Example of heatmaps of Danish and Norwegian gripping points overlapped with original image

Figure 3: Summary of the architecture after processing the trajectory prediction. Trajectory prediction is a heatmap of the included pig’s limbs in the gripper points from left side of pig leg.
Feasibility of Using NIR Spectroscopy in Automated Meat Cutting

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Abstract—Modern meat processing requires automation and robotization to remain sustainable and to adapt to future challenges. Optical methods, especially Near Infrared (NIR) spectroscopy, are well developed especially for minced meat analysis to verify its fat content. Feasibility of using NIR for real-time assessment of meat samples in automated meat cutting is assessed in this work. Lab experiments highlighted that it is possible to correlate fat and its thickness, muscle layers and bone of a fresh pork sample. Spectral analysis has shown to be an effective approach to separate different tissue types, however, further improved design of a robust optical probe for this purpose is necessary, so that to achieve a better selectivity with an easy classifier.

Keywords—Automation, NIR spectroscopy, Reflectance, Meat Industry, Robotic Arm

I. INTRODUCTION

Meat processing is an industry that requires novel automated solutions to remain sustainable and to mitigate harsh working conditions, shortage of skilled labour and not least, minimise impact of recent pandemic. Automation of all or many processes is seen as a the way forward, with robots performing various tasks instead of people.

This paper assesses the feasibility of using Near Infra-Red (NIR) spectroscopy for instant determination of a material type (skin, muscle, fat, bone) [1, 2] to assist in robotic cutting application, specifically focussing on pork case scenario.

II. THEORY

NIR spectroscopy uses electromagnetic spectra that falls in the range of 650 nm to 1100 nm. The light that enters the medium of interest (meat sample) may be either absorbed or scattered. As the speed of light changes in tissue, a beam with cycloid beam shape will be generated inside the tissue. The depth is thus dependent on the distance between the sending and receiving optical signal. NIR spectroscopy approach typically uses received information at a detector, and is affected by its position. As distance variation for sending and receiving NIR light is important, the practical realisation of the idea to send light at different distances and detecting it with the same receiver has not been achieved.

This work was supported by the EC H2020 projects “RoBUTCHER” grant agreement No 871631 and MSCA-ITN-ETN “MgSafe” under the Marie Sklodowska-Curie grant agreement No 811226.

III. METHOD

The experiments reported in this paper used reflectance type NIR spectroscopy, where both light source and detector are on the same side of a sample. Analysing the reflected NIR light received at a detector, it is possible to assess the nature of a tested sample in real time (fat, muscle, bone) to assist during an automated cutting process, as part of the robotic arm tool, next to or integrated in a cutting tool. Two different probe designs were tested as shown in Figures 1(a) and (b). In Avantes probe light from the source is transmitted via fibre optic cables. A standard halogen light source (Avantes light source) was applied and it required a warm up time of 15 min. Optical fibres were arranged in a circular shape with a diameter of about 1 cm (4 mm inner core). Another fibre with a dimension of 1 µm is placed at the middle of the probe to detect reflected light from the samples.

In second probe, designed at the OsloMet lab, there is a provision to obtain varying distance of 6 mm and 8 mm, by employing two light sources and one detector between them. An optical fibre is connected to a detector to pick up a reflected light from the tissue. To compare the effect of source-detector distance, maximum distance (8 mm) was used in the testing process. Thus, the source detector distance in latter is 8 mm, while that of a former is effectively less than half of it. Avantes spectrometer was applied for observing the reflected light from samples. Figure 1c shows the capture of spectra in Avantes software Avasoft, in the range of 600 nm to 1100 nm. Avantes spectroscope needs to be calibrated before taking the measurements for ensuring reliable results. Calibration is done by taking light and dark reference. Then one must ensure that a reflectance of the same reference surface is close to 100 percent before proceeding with actual measurement.

A freshly purchased pork sample containing bone, fat, and muscle tissue was used for testing, different parts of which are marked as shown in Figure 2. The temperature in the lab during measurements was maintained at 21±0.5 °C. Both
probes were tested on the same meat sample. At each point, 10 measurements were taken to verify the repeatability of the results. During the measurements it was made sure that the pressure on the meat sample is not deforming sample area. Intensity of light sources was kept below their saturation levels for the spectrometer for both probe types.

Figure 2. Different areas selected for NIR measurements.

IV. RESULTS

The NIR measurement data were first logged into an Excel file and then imported in Unscrambler X (Camo, Norway). The data were transformed into absorbance spectra by spectroscopic tools in the program. The absorbance data was further filtered for scattering with multiplicative scatter correction algorithm (MSC). A Principle component regression (PCR) analysis was performed on both data sets. The PCR models for both probes were then evaluated with the software.

By using multivariate analysis methods it is possible to predict the nature of sample tested. Principle component regression is one of the well known methods to visualize the information in the data set. In matrix representation, the model with a given number of components has the following equation (1):

\[ X = SL^T + E \]

where \( S \) is the scores matrix, \( L \) the loadings matrix and \( E \) the error matrix. The combination of scores and loadings is the structure part of the data. What remains is called error or residual, and represents the fraction of variation that cannot be interpreted.

Spectroscopy data of meat that can be collected using such arrangement can be used for analysing meat properties.

Figure 3. (a) Score plot of Lab probe (b) Score plot for Avantes probe.

The developed lab probe showed clear separation of all the data with different component in Figure 3(a). The interesting part is that it shows that fat 0 mm is close to muscle which again is the relation between data. Other fat layers with different thickness are close to each other, but still separable. The circular Avantes probe showed only the bone sides as separate entities (Figure 3(b)).

Figure 4 illustrates repeatable reflectance measurements taken in the same sample location. It shows that both instruments deliver highly repeatable measurements. Distinct reflectance measurements for fat, bone, and muscle are illustrated in Figure 5, while fat-muscle boundary is depicted in Figure 6.

Figure 4 Repeatability measurement (a) Lab prototype probe (b) Avante probe.

Figure 5 Comparing main segments of pork in range 700 nm to 1000 nm (a) Lab prototype (b) Avantes probe.

Figure 6 Fat Muscle boundary for (a) Lab prototype probe (b) Avantes probe.

V. DISCUSSION

The highly repeatable reading that are non-invasive in nature supports the feasibility of using NIR spectroscopy in meat industry during automated cutting processes for pork tissue type determination. NIR measurement have provided distinct reflectance signals when bone , muscle and fat were tested. It is interesting to note that prototype developed in OsloMet lab was able to respond with distinguishable peaks based on varying thickness, as especially evident in the NIR signal range of 900 nm to 1000 nm. This could help to correlate fat content in carcass with predictive model to assist during robotic cutting.

VI. CONCLUSION

Two NIR probes were evaluated for their feasibility as assistive tool for real-time pork tissue type determination in automated cutting applications. Based on the experimental results of the same pork sample, our developed lab-prototype probe with varying light source distance was more sensitive in NIR region, as to compared to a commercially available Avantes probe in the same region. NIR spectrometry could be considered to assist during an automated cutting process, as part of the robotic arm tool. The cutting tool fitted with such NIR optical probe, can assist robot in the automation process. Using these, a supervised machine learning model can be developed into a system which can be used to improve decision-making for cutting pathways prediction in roboticised cutting. However, further developments are needed to ensure that the probe design, data measurements and analysis are in line with the meat industry requirements.

REFERENCES


Feasibility of Using NIR Spectroscopy in Automated Meat Cutting

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OVERVIEW
✓ Optical methods @ Near Infrared (NIR) spectroscopy.
✓ Feasibility of using NIR for real-time assessment of meat samples in automated meat cutting is assessed.
✓ Lab experiments to correlate fat and its thickness, muscle layers and bone of a fresh pork sample.
✓ Spectral analysis is widely used in meat industry.
✓ Improved design of a robust optical probe for this purpose is necessary.
✓ Used reflectance type NIR spectroscopy.
✓ Two different probe designs were tested & compared.
✓ Unscrambler X was used for analysis.
✓ spectrometer supported by Avasoft software

CONCLUSION
❑ Developed lab probe showed clear separation of all data with different component (with accuracy of 87%)
❑ Prototype developed in OsloMet lab was able to respond with distinguishable peaks based on varying thickness
❑ Highly repeatable readings & non-invasive in nature supports feasibility of using NIR spectroscopy in meat industry during automated cutting processes

REFERENCES

ACKNOWLEDGEMENT
This work was supported by the EC H2020 project “RobButcher” grant agreement No.871631 and MSCA-ITN-ETN “MgSafe” under the Mariakiłdowska-Carie grant agreement No 811228.

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Table of Sample Locations

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<tr>
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<td>9 mm fat close to 1 cm thick</td>
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<tr>
<td>Fat</td>
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<td>4 mm fat muscle boundary</td>
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<td>Bone</td>
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<tr>
<td>Bone</td>
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<td>Hard bone structure side position</td>
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Fig. 12 : Anna (Master student) and Wajahat (PhD candidate) collecting data in OsloMet lab using Avantes probe.

Fig. 1 and 2: Tested NIR probes

Fig. 3 : 11 different test points (Table gives further details)
Human-Robot Collaboration in the Meat Industry

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Abstract— An approach to some production steps in the secondary red meat processing can be revised to improve human working conditions and food safety. Some of the meat processing steps are difficult to automate due to the tasks’ nature, but, taking into account the emergence of new technologies, especially in development of collaborative robots and recent advancements in the artificial intelligence (AI), it seems to be possible to solve these challenges in the near future.

Keywords— meat production, robots, automation, human-robot collaboration, HRC, human-machine collaboration, HMC

I. INTRODUCTION

The Covid-19 world pandemic hit most of the manufacturers regardless of industry and can lead to a future economic crisis. Among those who faced its consequences more than others are the meat producers. In the past year, there were many examples of factory closures due to cases of the virus among workers. Production specific requirements, for most process steps, imply people standing close to each other on the production line. It would be possible to avoid this situation if some of the steps had been automated to reduce the number of workers involved in the production. The meat industry is quite conservative when it comes to automation. One of the reasons is that existing automation systems are aimed at large-scale meat processors. Such systems do the job efficiently, but in most cases, they require large spaces for installation, can handle only one specific task per machine or station, and cannot be effectively scaled.

Despite the fact that there are positive trends in automation in the red meat industry [1], they mainly affect the primal meat processing (stunning, exsanguination, evisceration, carcass splitting, etc.) [2], or use automation techniques that were transferred from other industries, such as labelling, to provide traceability, packaging, etc. When it comes to the secondary meat processing (fat trimming, deboning, portioning, slicing, etc.), even relatively big meat processors still use manual approach to handle the meat.

II. HUMAN WORKING CONDITIONS

Meat processing requires maintaining low-temperatures inside the processing area. Temperature can vary depending on the type of meat and legal requirements regarding the processing procedure. For example, in the EU, according to EC No853/2004 [3] ambient temperature in the processing area cannot exceed 12°C. That is not a very comfortable temperature for human workers.

On top of that, work with sharp tools, heavy animal body parts and wet surfaces increase the chance of injury. These risks are typical for any industry, but in the long term every meat-industry worker is at risk of several occupational diseases.

According to the recent studies [3, 4], the meat industry workers often suffer from a number of occupational joints diseases. This problem is quite common in the industry, so some of the meat processing companies provide their workers with physiotherapy to reduce the risk of possible complications. All this leads to a growing shortage of workers in Europe for this sector.

III. CHALLENGES IN THE SECONDARY MEAT PROCESSING

There are few challenges in the secondary meat processing that make obstacles on the way to make the automation effective, robust and affordable for every meat processor:

1. It requires high precision and dexterity in performing such actions as cutting, deboning, fat trimming, etc., from a butcher.

2. Every meat piece has different size and form, as opposed to, for example, automotive industry, so its form is unknown at the moment it goes onto a conveyor belt, and it cannot be compared with a computer model from a database, using simple computer vision techniques, to perform further manipulations on it. More advanced approaches are required.

3. Meat is heterogenous (e.g., consists of different tissues, such as fat, muscles, ligaments, etc.), and in general, it is difficult to manipulate an object which is not solid [6] with a machine that has a limited degree of freedom of movement.

To deal with the challenges listed above in an effective way, an automation system should have a robust real-time feedback from a tool and have a computer-based vision system, to be able to determine a work object’s shape, predict the most efficient cutting trajectory, etc.

IV. RECENT ADVANCEMENTS IN AUTOMATION

Using robots in production lines became a reality in many industries. In the automotive industry they are used for such tasks as assembly, welding, painting, etc. Moreover, nowadays robotics goes beyond just performing repetitive tasks, and a concept of human-robot collaboration has appeared as one of the possible features of the Industry 5.0 concept [7].

Some of the companies that specialise in automation solutions and robots are shifting their focus from regular robots or robotic manipulators to a collaborative one. Presentation of new collaborative robot series GoFa and SWIFTI made by ABB in February 2021 [8] shows that it is an area in which the manufacturers are ready to invest. It
increases the competition between ABB, Kuka and Universal Robots, and will make collaborative robots more affordable and easier to work with.

Human-robot collaboration (HRC) combines classical robotics with AI and its main goal is to combine efforts of robots and humans to achieve a shared goal. HRC is not limited only to robotic arms. Another good example of such collaboration can be exoskeletons that provide assistance and physical support for workers. SuitX produces several series of them [9] that cover the whole body or one of its parts, to reduce the task specific load. Exoskeletons find their application not only in production, but also in healthcare.

Implementation of HRC is different for each industry, but the concept doesn’t change. Robots must interact with people in a safe and a smart way. An assembly process can be a good example of such collaboration, that already has place in production. From relatively simple tasks as wheel hub assembly [10], to improve work space ergonomics and reduce the risk of injuries, to more advanced examples, such as assisting in electrical cabinets assembly for workers with cognitive disabilities [11].

HRC opens up new opportunities for revising many production steps for which automation seemed to be difficult or even impossible due to peculiarities of the production process.

V. Concept of an Automation System

The transition from manual secondary meat processing to a fully automated one cannot happen immediately, and one of the keys to this transition could be human-robot collaboration. Robots are already accepted in the production lines by many companies outside of the meat industry. However, many cases the same solutions cannot be easily transferred to the meat industry because of the industry specific tasks and lack of knowledge base (no strict rules can be applied to the processing algorithm) necessary to solve the industry specific challenges.

At most of the meat processing plants the secondary meat processing is performed on a conveyor (so called paceline) with workers standing next to the line and performing the necessary operations on a meat piece.

Introducing collaborative robots into meat processing and using HRC principles would enable building a platform to accumulate knowledge necessary to build a fully autonomous system at an early stage. A basic concept of a system which incorporates a blended approach, consisting of both robots and human workers in a pace-line scenario, is represented in Figure 1.


The implementation of such a system will reduce the need for workers in the most mundane, repetitive or high-risk tasks on meat production lines. It will also reduce the density of workers in the future, enabling manufacturing to be more resilient in the face of pandemics like Covid-19. Furthermore, the skillset required in meat production plants will evolve, with more workers with higher education levels in AI and robotics required. Finally, benefits in production may be possible, including increased yield, higher through-put and greater consistency.

References


Human Robot Collaboration in the Meat Industry

Short term
- Covid-19
- Labour shortage (poor working conditions, low temperature at the processing area, job related musculoskeletal disorders, high risk of injuries)

Long term
- Low product margin, high competition between producers
- Food safety restrictions

World meat market

Challenges for meat processors

Primary red meat processing

Secondary meat processing

Examples of HRC\(^1\) and HRI\(^2\) in other industries

- Medicine
  - Minimally-invasive surgeries (ROBODOC, Zeus, ProBot, Da Vinci)
  - Robot assistants for people with physical disabilities
  - Robotics for physical therapy
- Cars assembly lines
  - Robot guidance for assembly tasks

Existing solutions in automation

Challenges in the secondary meat processing

Tools and technologies available

- Industry 4.0 technologies
  - Internet-of-Things
  - Big Data
  - Model based approach to production
  - Robotics
- Collaborative robots produce by Universal Robots, ABB, KUKA, etc.
- Virtual reality tools

Challenges to be solved

- Knowledge transferring from a butcher to a robot
- Cutting tissue’s type determination
- Meat piece manipulation (gripping and holding)
- Cutting trajectory planning
- System compliance with industrial safety and food safety requirements

Human Robot Collaboration in the Meat Industry

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\(^1\)HRC – Human-Robot Collaboration
\(^2\)HRI – Human-Robot Interaction

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EC H2020 project
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\*data provided by Food and Agricultural Organization of the United Nations (FAO)
Intelligent Cutting System for an Innovative Meat Factory Cell

Ian de Medeiros Esper, L. E. Cordova-Lopez, Pål J. From and Alex Mason

Abstract—This paper presents work relating to an intelligent cutting system for pig carcasses. It generates the cutting trajectories based on the meat factory cell cuts. A 3D point cloud is generated from RGB-D cameras placed arbitrarily in pairs on either side of the pig. The challenge for complete object reconstruction with little or no overlap and a high degree of symmetry is solved using a novel pipeline, then the 3D object is aligned to an atlas of the pig that encompasses the pig’s skin, bones, organs, and the desired cuts.

I. INTRODUCTION

Automation in a high throughput plant might be suitable, whereas in smaller markets a new approach should be considered, as the high starting and running costs of a robotised line are not affordable to these plants [1]. Summed to the harsh environment as a combination of hazardousness and the strenuous work explain, the labour shortage at the meat industry and act as a technology booster [2], [3], [4], [5], [6], [7].

To change the long time paradigm of production line in slaughterhouses, a cell area where the whole carcass is processed called "the meat factory cell" was proposed [8], [1]. Merging this concept with the flexibility of robots to perform different tasks, this work aims to research a novel intelligent cutting system.

II. MATERIAL AND METHODS

To accomplish the task of segmenting the carcass into the primal cuts, different and interdisciplinary subjects have to be applied. The Diagram in Figure 1 shows the workflow to accomplish the generation of the cutting trajectories.

A. Data Capture

To capture data at traditional (manual) slaughter lines in Norway, a simple system of four cameras was designed as seen in Figure 2.

B. Point Cloud Registration

As shown, the cameras are in sets (two-by-two); the cameras that share the same tripod have a good overlap, thus the sample consensus pre-rejective algorithm was used, achieving a good result.

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L. E. Cordova-Lopez, P. J. From and A. Mason are affiliated with the same institution as the corresponding author. Additionally, A. Mason is affiliated with Animalia AS, Oslo 0585, Norway (luis.eduardo.cordova-lopez@nmbu.no; pal.johan.from@nmbu.no; alex.mason@nmbu.no)
However, the cameras that are in different sets have more degrees of freedom and almost no overlap. Added to that, both sides have a very symmetrical shape making it impossible to use an algorithm to find matching points between the point clouds. A novel method was designed and the diagram in Figure 3 shows the steps to solve the challenge. Figures 4, 5 and 6 shows the output of the steps.

C. PigAtlas and 3D Reconstruction of the pig

PigAtlas is an atlas of the pig body structure using in-vivo computerized tomography data [9]. The model has the collection of tissues from the skin to the skeleton, and for this project, the cuts were included in the atlas.

The point cloud captured and processed in the step before is then rescaled and aligned to the PigAtlas skin vertices, giving the transformation for all the atlas parts, including the cuts. The result can be seen in Figures 7, with the point cloud of the pig and the atlas cuts in green.

The validation was made by measuring the length of the lower bar of the CHU and the diameter of the belly of the carcass, as seen in table I. Work is on-going, as far as possible with covid-19, to provide additional data to validate the approach.

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<tbody>
<tr>
<td>CHU Bar</td>
<td>2308mm</td>
<td>2248mm</td>
<td>60mm (2.6%)</td>
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<tr>
<td>Carcass Dia.</td>
<td>358mm</td>
<td>356mm</td>
<td>2mm (0.8%)</td>
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III. CONCLUSIONS

This work described a novel solution to generate the cutting trajectories using RGB-D cameras and the PigAtlas model. It reconstructs the point cloud of four cameras, set two-by-two, standing in an arbitrary position, and align this point cloud to the PigAtlas. This has been shown to generate at least the first set of cuts in the meat factory cell approach. Further investigation is needed to understand if the internal cut trajectory will be sufficient or another correction step will be needed.

ACKNOWLEDGMENT

This work was partially supported by the Research Council of Norway through the funding to the “MeaTable - Robotised cells to obtain efficient meat production for the Norwegian meat industry” project no. 281234. The work is also, in part, supported by the EC H2020 project “RoBUTCHER” grant agreement no. 871631.

REFERENCES

Introduction:
Automation in a high throughput plant might be suitable, whereas in smaller markets a new approach should be considered, as the high starting and running costs of a robotised line are not affordable to these plants. Summed to the harsh environment as a combination of hazardousness and the strenuous work explain, the labour shortage at the meat industry and act as a technology booster.

To change the long time paradigm of production line in slaughterhouses, a cell area where the whole carcass is processed called “the meat factory cell” was proposed. Merging this concept with the flexibility of robots to perform different tasks, this work aims to research a novel intelligent cutting system.

Materials and Methods:
To accomplish the task of segmenting the carcass into the primal cuts, different and interdisciplinary subjects have to be applied. The Diagram in Figure 1 shows the work flow to accomplish the generation of the cutting trajectories.

Point Cloud Registration:
As shown, the cameras are in sets (two-by-two); the cameras that share the same tripod have a good overlap, thus the sample consensus pre-rejective algorithm was used, achieving a good result, as seen in fig.

However, the cameras that are in different sets have more degrees of freedom and almost no overlap. Added to that, both sides have a very symmetrical shape making it impossible to use an algorithm to find matching points between the point clouds. A novel methods was designed as shown below.

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PigAtlas is an atlas of the pig body structure using in-vivo computerized tomography data. The model has the collection of tissues from the skin to the skeleton, and for this project the cuts was included in the atlas.

The point cloud captured and processed in step before is then rescaled and aligned to the pigatlas. The result can be seen in Figure 5, with the point cloud of the pig and the atlas cuts in green.

Conclusions:
This work described a novel solution to generate the cutting trajectories using RGB-D cameras and the PigAtlas model. It reconstructs the point cloud of four cameras, set two-by-two, standing in an arbitrary position and align this point cloud to the pigatlas. This has shown to generate at least the first set of cuts in the meat factory cell approach. Further investigation is needed to understand if the internal cut trajectory will be sufficient or another correction step will be needed.

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Data Capture:
To capture data at traditional (manual) slaughter lines in Norway, a simple system of four cameras was designed as seen in Figure 2.
Key Point detection in automated meat processing*
J. B. Andersen, D. B. Nielsen, L. B. Christensen

Abstract — Employing a robotic solution in meat processing to assist the highly trained operators in cutting operations requires development of means to support the powerful robots with a certain level of intelligence to cope with the biological variability present in modern slaughter facilities. Here, we present an AI-based vision approach intended for assisting a robot in separating a spine joint on a split pig carcass by automated identification of a specific vertebra.

I. INTRODUCTION

In recent years there has been a further research in robotic solutions to assist operators in more delicate yet repetitive operations as cutting and trimming the carcasses. This development has highlighted the need for developing sensor-based control of the operations to feed a more intelligent and adaptive procedural control software. The RoBUTCHER project [1] is focusing on this research topic. The approach is to include 3D vision cameras to cover and survey the working zone of the robot. The ambitious goal of the project is to use the cameras to measure the surface of a carcass, identify the limbs from their stitched point clouds and to train an artificial network to identify the position and pose of important details, e.g. limbs or joints. The latter is the topic in the present paper.

The procedure of interest here is the separation of a spinal joint of a chilled and longitudinal split pig carcass with a robot mounted tool, see Fig. 1. Separation of the joint is prerequisite to the consecutive cutting procedure through the soft tissues of the carcass. To reduce the risk of forming bone fragments left on the products a separation tool is tested in several projects and therefore it is chosen for the joint of interest here.

![Fig. 1. Example of a lumbar and sacral part of the spine of a split carcass. The joints between the vertebrae are the preferred clipping positions to reduce the risk of forming bone splinters in the final products.](image1)

The design of the clipping tool and the joint anatomy leads to a different required accuracy of the tools position in the different anatomically directions, see Fig. 1 and 2. Higher accuracy is required in the vertical direction (cranial-caudal) compared to the horizontal (dorsal-ventral) position in Fig 1.

II. MATERIALS

A. Image acquisition

Two 3D cameras (Kinect Azure) are positioned above the two half carcasses, surveying the rear (caudal) and the front (cranial) part, respectively (see Fig. 2). With this setup we made an image stack from 600 carcasses selected from a commercial Danish slaughterhouse. The selection forms a representative sample with respect to weight and length of the Danish pig population anno 2020.

B. Annotation

The joint annotation is made using the CVAT framework and Datumaro file format [2] by one single expert operator. The annotated dataset is divided into three subsets: A training, a validation, and a test set, with ratio 80:10:10, respectively. The test set is never seen by the model and used for the final performance test of the algorithm. In Fig. 3 an example is given.

![Fig. 2. Kinect Azure camera view from the acquisition set up. The sagittal splitting line is visible in the FOV of both the left and right caudal part of the chilled carcass. The upper part of the image show the position of the operating robot base.](image2)

![Fig. 3. Annotations, highlighted with green lines, on a sample from the training set.](image3)

C. Residual Neural Network

For our experiment we used a residual neural network (RNN), ResNet-18 [3], available in PyTorch [5], with weights from the model pretrained on ImageNet [4]. The model is modified such that the final layer outputs the four neurons representing a prediction of the two coordinate sets of the specific joint on a half carcass, which we wish to determine.
III. METHODS

Two ResNet-18 models are trained on the dataset, using two different loss functions. One being the Mean Squared Error (MSE) [6] computing the average squared Euclidean distance between predicted and target (annotated) points, i.e. a symmetrical loss function. For the second model we use a loss function which takes features of the cutting tool and carcass anatomy into account. This is done by splitting the MSE-loss into two separate parts. One handling errors parallel to the target line, and one handling errors perpendicular to the target line. By rotating and translating the cartesian coordinate system such that the $x$-axis lies on the target line, we end up with a coordinate system where $x$ and $y$, respectively, are parallel and perpendicular to the target line, and the positive $x$-direction is towards the spine. To reduce the impact of biological variability in spine joint size the loss in $x$ is expressed in coordinates, normalized with the individual spine size i.e., the separation between the target points.

IV. RESULTS

The results presented here, show how the trained and evaluated models perform on the unknown test dataset. Here the $S$-model denotes the model trained and evaluated with symmetric (MSE) loss function and the $A$-model denotes a model trained and evaluated with asymmetric loss function. Error in $x$ represents errors parallel to the target line, whereas $y$-error represents error perpendicular to the target line.

<table>
<thead>
<tr>
<th>TABLE I.</th>
<th>DIRECTIONWISE ERROR DISTRIBUTION WITH SYMMETRICAL LOSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prediction error</td>
<td>Symmetrical model</td>
</tr>
<tr>
<td>$x$</td>
<td>0.03cm</td>
</tr>
<tr>
<td>$y$</td>
<td>0.35cm</td>
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<tr>
<th>TABLE II.</th>
<th>DIRECTIONWISE ERROR DISTRIBUTION WITH ASYMMETRICAL LOSS</th>
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<tbody>
<tr>
<td>Prediction error</td>
<td>Asymmetrical model</td>
</tr>
<tr>
<td>$x$</td>
<td>$-0.72cm$</td>
</tr>
<tr>
<td>$y$</td>
<td>0.37cm</td>
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<table>
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<tr>
<th>TABLE III.</th>
<th>DISTRIBUTION OF POINTS PREDICTED ON THE SPINE SURFACE</th>
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<tbody>
<tr>
<td>Percentage of points predicted to be in the spine</td>
<td>$S$-model</td>
</tr>
<tr>
<td>53%</td>
<td>6%</td>
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</table>

V. DISCUSSION

The effect of introduction of anatomical based loss functions is clearly seen in Table I and II. Due to the asymmetrical loss in $x$ direction, the model tends to prefer prediction points placed outside the rigid spine structure. The mean offset is predicted to less than one centimeter leaving ample room for the spine joint to be placed within the aperture opening of the clipping tool. The $y$-direction show no significant difference between the two models. The model trained with an asymmetric loss function thus provides a more robust solution with respect to the anatomy of the pig and the features of the cutting tool. In Table III the models are compared by the number of points predicted on the rigid part of the spine. Such situations result in erroneous process as the tool needs to enclose the joint to perform the separation. The improvement from 53% to 6% shows the beneficial introduction of the asymmetric loss function.

![Fig. 4. An illustration of the predicted points on a test carcass. In blue the symmetrical model and in green the asymmetrical model compared to the operator annotations in black. The specific errors are given above the images ($p_d$ being the dorsal point and $p_v$ the ventral). The lower image is a zoom of the area of interest, shown for clarity.](image)

ACKNOWLEDGMENT

Our colleague Peter Vorup is acknowledged for his careful annotation, Max Petersen for his selection of representative carcasses and assistance to the image acquisition and finally Kristian Damlund Gregersen for sharing the images.

REFERENCES

Objective
As a part of the RoButcher project the focus is on developing sensor-based control of carcass cutting and trimming operations. We use an artificial neural network to identify position and pose of important details such as limbs and joints. The focus here is to create a method that robustly determines the inter-vertebral joint of interest for separation of a spinal joint of a chilled and longitudinal split carcass.

Carcass anatomy and tooling geometry
One of the single most important things for the clipping tool to do, is to cut through the entire spine disk between vertebral. An error perpendicular to the joint will result in the cut going through a solid vertebra and a prediction on the spine surface causes a cut that does not go through the entire spine disk, as the tool will recoil on the rigid spine surface. A prediction further away from the spine will result in a cut through the entire spine and some extra tissue, hence this is the most favorable error.

Loss functions in relation to carcass anatomy
To meet the different costs on error types presented above we have created a loss function based on the carcass anatomy and tooling geometry. The loss function splits the errors into two directions: x- and y-direction, parallel and perpendicular to the target line, respectively.

\[
L = w_1 \sum_{i=1}^{N} (x_{\text{target}} - x_{\hat{\text{target}}})^2 + w_2 \sum_{i=1}^{N} (y_{\text{target}} - y_{\hat{\text{target}}})^2 + w_3 \cdot \cos(y),
\]

where \(w_1, w_2, w_3\) are given weights, \(x_{\text{target}}\) is a second order polynomial, and \(x_{\text{target}}\) is a piecewise function of second order polynomials. \(y\) is the angle between the target line and the predicted line.

Results
The results presented here show the distribution of prediction errors parallel (\(x\)-error) and perpendicular (\(y\)-error) to the target line, for a model, S-model, trained with standard MSE loss function and, A-model, trained with the asymmetric loss function proposed here. The negative direction of \(x\) is away from the spine, and positive direction is into the spine. The final lower table shows the percentage of points predicted on the rigid spine surface.

Discussion
The effect of introduction of anatomical based loss functions is clearly seen in the predicted error is along the anatomical directions. Due to the asymmetrical loss in \(x\)-direction, the model tends to prefer prediction points placed outside the rigid spine structure. The mean offset is predicted to less than one centimeter leaving ample room for the spine joint to be placed within the aperture opening of the clipping tool. No significant difference is seen in \(y\)-error.

*Research supported by EU funded Horizon2020 RIA Project, Grant agreement ID: 871631 under the topic ICT-10-2019-202: Robotics Core Technology.
The role of Digital Innovation Hubs in promoting new technologies

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Abstract—Digital Innovation Hubs offer various services, as well as opportunities to present the work and achievements of meat industry automation. These projects should also work with the hubs to identify transferrable knowledge to other sectors. Furthermore, regular communication channels with the hubs enables discussion of challenges, and grants access to relevant competence where required, or to influence the topics of funded challenges set by the DIHs. Since the DIHs set up under DT-ICT-02-2018 are relatively new (some starting ca. January 2019), representatives of the meat sector should keep in touch with the relevant parties and use the developing knowledge to realise project-specific benefits. This abstract presents the DIH services related to the agro-food domain, particularly to the meat processing sector.

I. INTRODUCTION

The Digital Innovation Hubs (DIHs) are an independent platform within the European Union, spreading across regions, extensively relying on an international network of key partner institutions and companies. The system was proposed as a key priority in the Digitising European Industry Initiative, adopted in April 2016. DIHs act as distributed technology transfer centres of excellence, founded on the principals of a priori innovation hubs and living labs. In general, living labs are user-centric-, open-innovation ecosystems, integrating concurrent research and innovation processes within a public-private-people partnership. There has been seen strong differences in the level of digitalisation across the EU, depending on the sector and region, and DIHs are expected to bridge the current divide. To facilitate the operations of the DIHs, the EU has launched thematic calls in the past years to call for overarching umbrella organizations, also called DIHs. The most relevant such call was the DT-ICT-02-2018 - Robotics - Digital Innovation Hubs (DIH) [1].

DIH services and partner benefits include:

1) Networking and knowledge hub developing
2) Access to latest technologies via DIH associate partners
3) Prototyping, research and development, and/or manufacturing expertise to speed-up the development
4) Access to public and private funding to help transform innovative ideas into market-ready products
5) Helping innovators understand customer segments, regulations and value chains
6) Enabling product testing and service testing and validation in specialized labs and/or realistic test environments
7) Enable knowledge building both for domain professionals as well as technology developers
8) Link to end users, orchestrating pilots.

It is worth noting that although DIHs perform a range of common services, there are also differences in their structure, engagement mechanisms and “mission focus”. Thus, while the above list provides are general overview of the services and benefits on offer, these may be exaggerated to a greater or lesser extent depending on the DIH.
II. THE DIH LANDSCAPE

To help collaboration and networking with the DIHs, the Commission set up an online catalogue: an interactive map with over 300 operational DIHs. This helps the identification of hubs around Europe and facilitates networking as well as new project’s relevant initiatives. Searching this catalogue resulted in 37 DIHs for “agriculture” in their profiles and 66 for “food”. Most of the registered DIHs have been clustered in the recent call, DT-ICT-02-2018 - Robotics - Digital Innovation Hubs (DIH), and organized thematically. Out of the existing clusters, many may hold interest for collaboration over a meet industry related project, i.e. RoBUTCHER. For efficacy, the DIH clusters have been reviewed within this strategy. The following DIH clusters came to existence, see Table I.

Our work in primarily focused around innovation targeting the meat industry, aiming to provide new solutions within the RoBUTCHER H2020 project [3].

REFERENCES

Digital Innovation Hubs offer various services, as well as opportunities to present the work and achievements of meat industry automation. These projects should also work with the hubs to identify transferrable knowledge to other sectors. Furthermore, regular communication channels with the hubs enable discussion of challenges, and grants access to relevant competence where required, or to influence the topics of funded challenges set by the DIHs. Since the DIHs set up under DT-ICT-02-2018 are relatively new (some starting ca. January 2019), representatives of the meat sector should keep in touch with the relevant parties and use the developing knowledge to realise project-specific benefits.

Source: "Digital Innovation Hubs as technology accelerators" slides, Thessaloniki, 2017
Open Issues in Agri-food Robot Standardization—the Red Meat Sector

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Abstract—Safety of equipment, operator and the environment during robotic operation is paramount. Robotics is appearing in more and more professional service applications, while robots and robot systems are evolving fast themselves, yet the legislation and standards regarding these topics are lagging behind. In connection with the RoBUTCHER project—which is a pioneering research-project employing industrial robots for completely automated slaughtering—it was revealed that there is no particular standard regulating directly robotics applied to the agri-food application domain. More specifically, the meat industry and the red meat industry within has only seen hygienic standards regarding machinery, not considering human–robot collaboration or safe autonomous robot operation in the abattoirs. The purpose of this paper is to provide a general overview of the relevant standards (and similar guiding documents) that could be used as pathfinders during the development of inherently safe robotic systems. Exploring the standards and legislation landscape should offer some instrumental help regarding the foreseen certification process of meat processing robots and robot cells in the near future.

Index Terms—robot, meat processing, standardization, food robotics

I. INTRODUCTION

In the European Union (EU), the CE mark (Conformité Européenne) must be obtained, certifying that the product complies with the essential requirements of the relevant EU health, safety and environmental protection legislation. The approval procedure can be managed by the manufacturer (under the legal responsibility of the CEO), or by an independent certification body (called Notified Body, when registered in the EU). When a Notified Body assesses a system, their responsibility is to ensure the conformity of the product with the legal requirements (regulations) before being placed on the market.

Standards are always voluntary by default, based on an industry and academic expert consensus, codifying already existing good practices, methods and general requirements. Nevertheless, since they often mean the highest quality available structured set of requirements toward e.g., the safety of a type of system, standards are sometimes made the basis of regulations by lawmakers (e.g., the ISO/IEC 60601-1 became the basis of the EC Medical Device Directive). When Notified Bodies are dealing with a new system, they usually consider the non-compulsory standards’ recommendations as well during their system assessment, therefore manufacturers and developers should consider those from the early periods of development on, since certifications increase competitiveness. Increased autonomy of robotic systems has greatly ameliorated certification challenges, and only recently emerged standards have been able to address the safety concerns of those—in an application domain specific manner.

Standardization efforts have been extensive in the robotics domain for the past three decades [1]. ISO (International Organization for Standardization) standards have been traditionally providing guidance for safety in this domain and formed the basis of the European Commission Machinery Directive (EC MD) [2]. It has been a long professional debate to unambiguously define a robot and its components. The traditional ISO 8373 - Robots and robotic devices – Vocabulary standard under ISO first appeared in 1996, only referring to “Manipulating industrial robots”, later extended to all robots (in the ISO sense) [3]. The responsible Technical Committee (TC) 299 has revised its official definition numerous times in the past years to incorporate all new domains and forms of robots. Their key distinguishing factors are autonomy, mobility and task oriented behaviour. The current ISO definition of a robot being:

“programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation or positioning”,

wherein autonomy is defined as:

“ability to perform intended tasks based on current state and sensing, without human intervention” [4].

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Robotics is rapidly advancing in almost all possible application domains, now entering the agri-food industry as well [5]. The robot system of the mentioned RoBUTCHER project will carry out cutting and manipulation tasks supported by RGB-D cameras, AI, Virtual Reality and telemanipulation [6], [7]. However, the system will be even more complex from safety and legislation aspects. The robots will handle raw meat products intended for human consumption, therefore the risk of contamination is high due to the presence of the guts and intestines, and the applied end of arm tooling (EOAT) are designed for meat and bone cutting and gripping, making them highly dangerous for humans too. Given the current approach for classification, the robot cell would be considered as a professional service robot application, still falling under the Machinery Directive when considering ensuring safety of the system (Fig. 1).

II. METHODS & STRUCTURE

This review mainly covers ISO standards, since they are globally accepted, have been pioneers in the robotics field and commonly used in the industry, moreover ISO certification is often required by industrial customers due to its direct linkage to the European Commission’s Machinery Directive (EC MD). It is worth to mention however that ISO only develops the international standards and does not issue certificates, that is performed by external certification bodies. The two main possibilities – according to www.iso.org – are as follows:

- **Certification** – the provision by an independent body of written assurance (a certificate) that the product, service or system in question meets specific requirements.
- **Accreditation** – the formal recognition by an independent body, generally known as an accreditation body, that a certification body operates according to international standards.

Beside ISO standards, some related EU directives, guidelines and recommendations were also reviewed.

The clear and unambiguous use of the frequently occurring words and expressions in the robot industry is essential. ISO 8373 states that “This International Standard specifies vocabulary used in relation with robots and robotic devices operating in both industrial and non-industrial environments”, thus this document will use the words and expressions according to this ISO standard’s definitions [4]. ISO 8373 is currently under revision – a new version is in FDIS (Final Draft International Standard) status – thus some definitions may slightly change in the future.

III. DISCUSSION

While there are numerous robot safety standards for the traditional industrial applications, there are very few for the service robot domains, and technically none for the automated meat processing industry — or similar. To facilitate the clearance of the automated meat-processing plants (such as the RoBUTCHER Meat Factory Cell), safety considerations shall follow the general minimum hazard principle (identifying and reducing the hazards), based on the existing standards (Fig. 1).

It is likely that following the safety design principles of ISO 10218 standards family, a systematic solution can be given to most system structures. Nevertheless, the chosen Notified Body for certification might have other and additional requirements. The agri-food domain may well adapt existing safety requirement structures from other application areas, such as medical robotics, where the Degree of Autonomy and Level of Autonomy for a system have been linked to different safety requirements [8]. It is reasonable to assume that choosing the maximum safety control principle of the robot cell (e.g., teleoperation instead of collaborative control for exception management and manual override) significantly increases the future applicability/deployability of such developments.

REFERENCES


Open Issues in Agri-food Robot Standardization — The Red Meat Sector

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Abstract
Robotics is appearing in more and more professional service applications, while robots and robot systems are evolving fast themselves, yet the legislation and standards regarding these topics are lagging behind. It was revealed that there is no particular standard regulating directly robotics applied to the agri-food application domain. More specifically, the meat industry and the red meat industry within has only seen hygienic standards regarding machinery, not considering human–robot collaboration or safe autonomous robot operation in the abattoirs.

Autonomy

Conceptual setup of a collaborative (top) and an autonomous (bottom) MFC

Standards

- **ISO 8373:** “This International Standard specifies vocabulary used in relation with robots and robotic devices operating in both industrial and non-industrial environments”
- **ISO 12100:** Safety of machinery – General principles for design – Risk assessment and risk reduction
  » Overall framework and guidance during development of machinery to enable safe desings

Autonomy

- **ISO 11161:** Safety of machinery – Integrated manufacturing systems – Basic requirements
  » Describes how to apply more specific standards
- **ISO 10218:** Robots and robotic devices – Safety requirements for industrial robots
  » Part 1: “inherent safe design, protective measures and information for use of industrial robots”
  » Part 2: “basic hazards and hazardous situations identified with [robot] systems”
- **ISO 20218:** Robotics – Safety design for industrial robot systems Part 1 – End effectors
  » The manufacturing, design, and integration of end-effectors and preparation of a “instructions for use”

Two levels of PDCA cycle for food safety (ISO 22000)
Feasibility Demonstration of Robotic Limb Gripping

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Abstract—In this paper, we present the experimental tests of a custom-develop soft tissue manipulator aimed to support automated pig processing. The inner organs of the animals to be processed are mostly soft tissues, yet a universal gripper design enables versatile applications. Precise manipulation may be required for certain robotic processes, while robust design can significantly increase the grasping success ratio. The customized mechanical design and the force measuring feature allow safe grasping, holding, stretching and moving of tissues, including skin and bones within. During laboratory dry tests, we measured the maximum gripping force and load capabilities of the gripper. The tool was mounted on a UR 16e manipulator and tested on pig-carcasses in a local slaughterhouse as well. It was shown to be capable of handling large organs and managing heavy loads.

I. INTRODUCTION

This paper focuses on the mechatronic fulfilment of gripping and manipulation requirements in an automated Meat Factory Cell (MFC) setup [1]. During the envisioned robotic slaughter workflow, there are different types of grasping tasks identified, categorized as internal (organ) and external gripping. Traditionally, these required different (manual or robotic) tools for successful execution. During an internal organ removal, the gripper must be capable of reliably (i.e., firmly and safely) grasping the pluck (the set of the internal organs and intestines of a large animal), as well as interacting with the bowels to push or pull them away from the belly. External gripping means that the animal’s limbs need to be manipulated to assist the cutting of the ham. Tasks include the grasping, pulling, rotating, and eventually racking the front and rear limbs.

A. Laboratory dry test

A prototype of the first iteration of the gripper-design is shown in Fig. 1, attached to a Universal Robot UR16e manipulator. The maximum torque output was computed by measuring the gripping force. Fig. 2 shows the gripping force—time graph of a dry test. The closing fingertips reached the beam load cell at around T = 4 s. The maximum measured force was 19 N (1.7 Nm on shaft), but immediately after hitting the rigid load cell, the stepper motor started to lose steps. The remaining gripping force was about 16 N on the load cell (P1 in Fig. 2). After shutting off the motor—that was already stalled—about 10 N remained (P2), however, this value depends on the exact moment when the motor is shut down (e.g., the remaining force is much lower right after losing a step than before that exact moment). The oscillations around P3 are the results of trying to pull out the loadcell from between the fingers.

High load dry-lab tests were performed at the Antal Bejczy Center for Intelligent Robotics. The goal was to test the maximum load capacity of the gripper. The objective was to check before the on-site tests, whether the gripper can withstand the expected loads and forces. First, increasing weights were attached to the fingers by a rope (Fig. 1/a), simulating the load when all the inner organs (or whole legs) have to be carried to the rack by the gripper. The gripper lifted up the weight without any deformation or break, up to 16 kg (maxing out the load capacity of the UR16e robot employed...
for this experiment) with two load directions (parallel and perpendicular to the finger’s axis of rotation), meaning that the self locking mechanism is working as we expected, the gripper finger can stand much higher passive clamping forces. This is to provide stable shape locking. Additionally, a trachea phantom was made of silicone (including the larynx) to test whether the larynx gets stuck in the gripper as expected, even when the trachea starts to slip out. A successful grasp with additional weight attached to the phantom is shown in Fig. 1/b.

These tests resulted in important numerical information about the gripper’s power, torque and its limitations, however, the real task scenarios at a slaughterhouse are quite different. Because of the slippery surfaces of inner organs the clamping force can be relatively small, thus the gripping theory is based on shape locking, which is provided during inner organs (trachea–larynx) and whole limbs (ankle) grasping too.

B. On-site tests of the gripper

After laboratory dry tests, the gripper was tested at an experimental slaughterhouse belonging to Szent István University, (managed under local experts) on fresh pig carcasses as well. Pigs with different weights (65–110 kg) were involved to test the gripper’s limitations. The trachea grasping was successfully at all of the test subjects, but in one case—after pre-cut processes—significant amount of muscle remained around the trachea. The muscle has higher stiffness than connective tissue, thus the gripper reached its gripping force limit, i.e., it failed to compress the tissue enough to reach a firm shape-locking grasp. In conclusion, it was decided that a stronger motor should be used in the final gripper, and that the xy dimensions of the gripper should be reduced, since during grasping of trachea the space around the gripping target is very limited in the MFC setup. The trachea and limb grasping is shown in Fig. 3.

For the on-site testing, a 6 DoF force/torque sensor (Onrobot HEX-E QC https://onrobot.com/en/products/hex-6-axis-force-torque-sensor) and an orientation-sensor were connected to the gripper. The force/torque sensor—placed between the gripper and its handle—measured the external forces and torques acting on the gripper along 3–3 axes, while the orientation-sensor was used to align the force sensor’s coordinate system with the “pig’s coordinate system”.

Fig. 4 shows the resultant force acting on the gripper, after the diaphragm was already cut through, and all the intestines were tried to be removed only by pulling the trachea using the gripper. (This being part of the MFC workflow.) However, at a certain point (around T = 25 s) the trachea cracked, and ripped off the pluck from the intestines. At that point, more than 350 N was measured as resultant force, however, this data might be a little inaccurate, since the torque-limit of the sensor was already exceeded along one axis. This experiment showed that both the gripper and the trachea withstand the weight of all the inner organs (150—200 N), and that the gripper is stronger than the organs, which means that it shall not break during these tasks under any circumstances.

II. CONCLUSION

We presented the results of an ongoing development of a multi-purpose gripper, designed for large animal inner organ and external limb grasping and manipulation. The initial prototype was tested in a dry laboratory environment and also via on-site tests in an experimental slaughterhouse. Application driven system requirements were defined and fulfilled. Eventually, the gripper was re-designed to provide integrated, in-tool force/torque and slipping sensing features, in order to meet the safety requirements of a slaughterhouse application. A next generation of the multi-use gripper is under manufacturing now.

REFERENCES

Feasibility Demonstration of Robotic Limb Gripping

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Abstract

Soft tissue interaction and grasping is a widely researched field, nevertheless, autonomous robotics is a relatively new domain in delicate meat processing. The inner organs of the animals to be processed are mostly soft tissues, yet a universal gripper design enables versatile applications. Precise manipulation may be required for certain robotic processes, while robust design can significantly increase the grasping success ratio. The customized mechanical design and the force measuring feature allow safe grasping, holding, stretching and moving of tissues, including skin and bones within. During laboratory dry tests, we measured the maximum gripping force and load capabilities of the gripper. The tool was mounted on a UR16e manipulator and tested on pig carcasses in a local slaughterhouse as well. It was shown to be capable of handling large organs and managing heavy loads.

Laboratory dry test

- Maximum gripping force measurement
- Static load test parallel and perpendicular to axis of rotation
- Shape locking mechanism test with trachea phantom

On-site Test

- Tests at an experimental slaughterhouse
- Real pig-carcasses
- Pigs with different weights (65–110 kg)
- Successful gripping of trachea and all limbs

Measured gripping force between gripping finger tips

Load test

Shape locking mechanism test

Trachea gripping under larynx (left), limb gripping on Norwegian gripping point (right)
Abstract—The goal of our research is to present the objective analyses and optimization process of possible layouts for primary cuts during pig slaughtering using two robots in an envisioned robotic cell within the H2020 project RoBUTCHER. The complete layout consists of a gripping robot, a cutting robot and a Carcass Handling Unit (CHU). The aim of the particular optimization was to enable the robots to complete all pre-defined primary cuts and leg manipulation tasks on the pig while assuring maximum manipulation reserve.

I. INTRODUCTION AND CAPABILITIES

The most characteristic feature of robot applications is their layout design, this allows the implementation of the expected functionality [1]–[4]. Cell design is an iterative development, assuming physical characteristics and application/user requirements. This should be based on existing physical boundaries (workpiece weight, size, geometry, material, environmental effects). In addition, there is a need for financial considerations, consideration of available resources and their use, and optimization of costs.

A. Available physical assets

Within the RoBUTCHER project (https://robutcher.eu), the following parameters are considered given: 2 heavy-duty robot arms manufactured by ABB Robotics:

• Cutting Robot: ABB IRB 4600-40/2.55;
• Gripper Robot: ABB IRB 4600-60/2.05.

Workpiece (pig) assumed parameters:

• Weight: 80–90 kg; internal organs: 10–15 kg;
• Length: 1700 mm (including hams);
• Diameter: 360 mm (without hams and shoulders);
• Hams weight: 10–15 kg/pc;
• Shoulders weight: 8–12 kg/pc.

Fixtures and obstacles:

• Carcass Handling Unit (CHU), custom designed [5];
• Robot Stages.

II. LAYOUTS COMPARE

The initial cell layout was considered as the current design. The position of the robots relative to the piglet is shown in the RoboDK simulation program in Fig. 1 right.

Fig. 1. Initial Layout of the robot cell. Left: actual view at NMBU; Right: Simulated representation in RoboDK.

A. Problems and Solutions through the optimization process

1) Problem identification and description: Removing the left shoulder, the Cutting Robot is unable to reach the body for cutting movements without colliding with the top structure of the stand.

2) Recommended solution: Re-position the slaughter robot by placing it in the center on a 700 mm high stage. The pig processing with the new position of the Cutting Robot can be seen in Fig. 3.

3) Description of the first problem: The Gripper Robot is unable to grab the left shoulder in the correct position due to the limits of Joint 5.m senn in Fig. 4.

4) Recommended solutions: Re-position the Gripper Robot above the CHU upside-down, if possible. Considering the weight of the robot arm, the payload and the limits of the work space around the CHU.
5) **Recommended solutions:** It could also be another suitable solution to install one more robot with a gripper to the other side of the CHU if possible. Considering its financial implications. Furthermore, the removal of the left ham would also be smoother by using another robot in Fig. 5 left. To avoid using an extra robot, or hanging the Gripper Robot, it could also be a solution for the robots to exchange tools with each other. However, this scenario is not feasible either, because the new Cutting Robot cannot go deep enough to cut off the left shoulder without hitting the top part of the CHU.

6) **Description of the second problem:** After lifting the upper piece of the pig, the Cutting Robot is unable to approach the body for side cutting actions without colliding with the back element of the CHU as in Fig. 6.

7) **Recommended solution:** Analyzing the functions of the CHU, it is not necessary to fix the hams to the structure from the beginning of the robotic process, as the robot with a gripper itself fulfills this task during the workflow. As a result, the rear section of the stand is removable.

8) **Description of the problem:** In the second side cutting process, the previously detected problem appears again as the slaughter robot cannot avoid the top of the stand. For this reason, by choosing a different robot configuration, collisions can be avoided. However, in this case, the robot has to make wide turns with a knife in its flange to get to the prescribed position, which makes it extremely dangerous to its environment.

9) **Recommended solution:** Repositioning the Cutting Robot backwards by 250 mm, and reduce the height of its stage by 220mm fig7.

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**III. SUMMARY**

Given the above input parameters, The most suitable position for the Cutting Robot (ABB IRB 4600-40/2.55) is in the center on a 480 mm high stage and 3150 mm behind the first axis of the CHU.
Finally, the most significant problem that needs to be solved is the failure of grabbing the left shoulder in an appropriate position.

REFERENCES

The goal of our research is to present the objective analyses and optimization process of possible layouts for primary cuts during pig slaughtering using two robots in an envisioned robotic cell within the H2020 project RoBUTCHER. The complete layout consists of a gripping robot, a cutting robot and a Carcass Handling Unit (CHU). The aim of the particular optimization was to enable the robots to complete all pre-defined primary cuts and leg manipulation tasks on the pig while assuring maximum manipulation reserve.

The initial cell layout was considered as the current design. The position of the robots relative to the piglet is shown in the RoboDK simulation program in right.

Removing the left shoulder, the Cutting Robot is unable to reach the body for cutting movements without colliding with the top structure of the stand. Re-position the slaughter robot by placing it in the center on a 700 mm high stage.

Install robot with a gripper to the other side of the CHU if possible. Considering its financial implications. Furthermore, the removal of the left ham would also be smoother by using another robot.

Given the above input parameters, The most suitable position for the Cutting Robot (ABB IRB 4600-40/2.55) is in the center on a 480 mm high stage and 3150 mm behind the first axis of the CHU.

Initial data

The most characteristic feature of robot applications is their layout design, this allows the implementation of the expected functionality. Cell design is an iterative development, assuming physical characteristics and application/user requirements. This should be based on existing physical boundaries. In addition, there is a need for financial considerations.

Abstract

Alternatives

Summary