Optimizing Flow and Quality Control of Scampi

A. F. Gravgaard, F. K. Woldenhof, G. Randers, J. W. Knudsen, M. K. Aasted

Department of Materials and Production, Aalborg University
Fibigerstraede 16, DK-9220 Aalborg East, Denmark
Email: agravg19@student.aau.dk, fwolde21@student.aau.dk,
grande19@student.aau.dk, jknuds19@student.aau.dk
maaste21@student.aau.dk
Web page: http://www.mechman.mp.aau.dk/

Abstract

This paper focuses on optimizing the quality sorting process for scampi (Nephrops Norvegicus) at the Læsø Fiskeindustri processing facility in Skagen. A thorough analysis of the processing facility reveals that the manual quality inspection can be optimized. Manual labor is hard to acquire and is a concern for Læsø Fiskeindustri, why a conceptual automatic quality sorting mechanism has been developed. The concept revolves around implementing hyperspectral imaging for vision inspection of scampi, which needs certain requirements to be met. A mechanical system designed to meet these requirements and facilitate the vision inspection is developed to untangle and singulate the scampi through vibrations and accelerating conveyor belts. A risk assessment is made to conclude on the financial feasibility.

Keywords: Singulation, Quality Control, Automatic Grading, Vision and Hyperspectral Technologies, Vision Classification Models, Machine Learning

1. Introduction

This article has been co-authored by two project groups:

VT3.025-5 consisting of Jacob W. Knudsen and Andreas F. Gravgaard.

VT3.025-6 consisting of Mathias K. Aasted, Gustav Randers and Frederik K. Woldenhof.

Sections will be attributed to the respective group names. Any sections that are not explicitly attributed are the collaborative effort of both project groups.

Processing scampi (Nephrops norvegicus) can be a difficult task, especially in terms of handling and quality control. Scampi, as seen in Figure 1, is a type of lobster mainly found in the North Sea.

Fig. 1 Scampi processed at LF.

Læsø Fiskeindustri (LF) [1] is a Danish company that processes about 45% of these lobsters landed in Denmark. Currently, scampi handling and quality control are done manually at LF's facilities, which is unattractive as a work environment.

According to [2], one of the reasons for automating food processing is to reduce labor costs, address difficulties in finding new employees, and increase both the quality and processing rate of the food. These are the same issues that LF is currently facing in their scampi processing. If LF can achieve a higher degree of automation, they are likely to save money and improve the consistency and flexibility of their processing operations. This would also allow for easier adjustments to the varying input.

1.1 Case Description

Scampi is a perishable product that requires quick processing. These are brought to the facility in large boxes and emptied into the processing line. Then LF dips the scampi in a bath, sorts them, and freezes them to maintain their freshness for consumers. This study provides a description of the processing line, identifies the challenges faced by LF during the analysis, and guides the selection of the problem to be addressed.

A schematic of the processing facility in Skagen is illustrated in Figure 2, where the scampi are rinsed, quality sorted, weight graded, arranged, freezed and packed in 800 grams retail packages. Three workers are responsible for the manual quality sorting. It is a tough job, where the workers get worn down over time from the required straining movements.

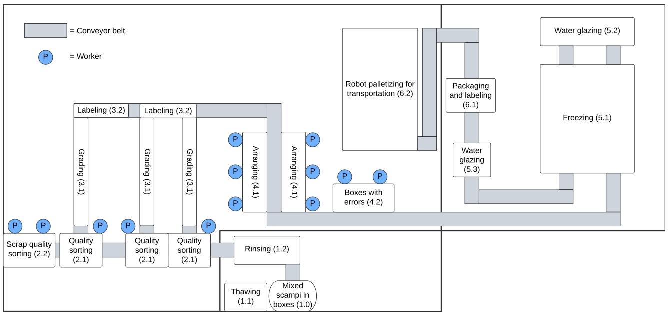

Fig. 2 The Processing Line at LF.

The flow of the quality sorting is illustrated in Figure 3. The scampi not approved at the initial 'Quality Check 1' will go through a second 'Quality Check 2', where they are sorted based on the quality of the scampi tail.

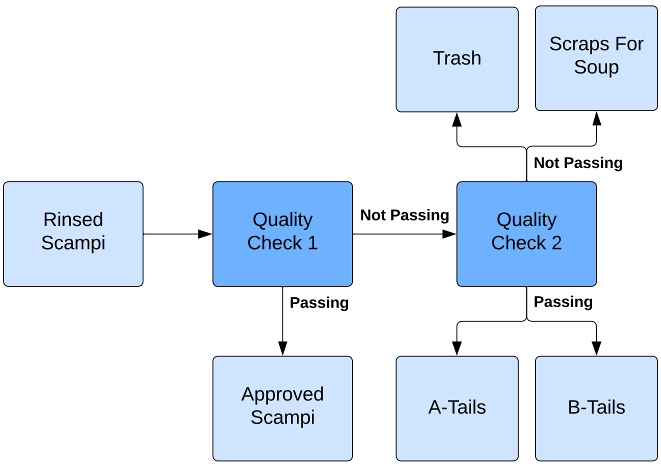

Fig. 3 The Quality Inspection Flow.

The objective is to replace the manual quality sorting at 'Quality Check 1' with an automatic solution using vision and hyperspectral technologies. The objective is split in two parts: Developing the models for the vision and hyperspectral inspection, and designing a mechanical system facilitating the vision inspection.

The quality criteria utilized during manual quality sorting are listed below:

1) **Quality check 1**
   - Spoilage
   - Foreign objects
   - Sand
   - Soft shell
   - Ruptured roe in head
   - Missing both claws
   - Missing legs
   - Missing eyes
   - Broken back
   - Cracked head
   - Dark color
2) **Quality check 2**
   - Spoilage
   - Foreign objects
   - Sand
   - Soft shell

Project group VT3.025-5 is responsible for the vision- and hyperspectral technologies in the following.

Project group VT3.025-6 is responsible for a mechanical setup facilitating the vision inspection in the following.

2. Methodology

The methods used throughout the article will be stated.

2.1 Value Stream Map

Value Stream Maps [3] have been utilized to compare the current production to implementation steps towards an automated quality sorting in terms of e.g. non-value adding time (waste), value adding time, production capacity, and potential bottlenecks. The Value Stream Map provides an organized overview of the facility, which give an insight into the production setup, overhead, and relation to customers and suppliers.

2.2 Discrete Event Simulation

Discrete event simulation is a method used to simulate real world systems by a set of separated processes, which are combined and progress through time. It can be used to locate bottlenecks and determine the utility of a given process. When implementing a new process, it can evaluate the performance to conclude on how much impact a new process will have for the rest of the system [4].

2.3 K-Nearest Neighbors

K-Nearest Neighbors (KNN) is a simple classifier based on points in space. For the sake of simplicity, the algorithm will be described in a two-dimensional space.

When training a KNN model, the points are simply stored in memory, as visualized in Figure 4.

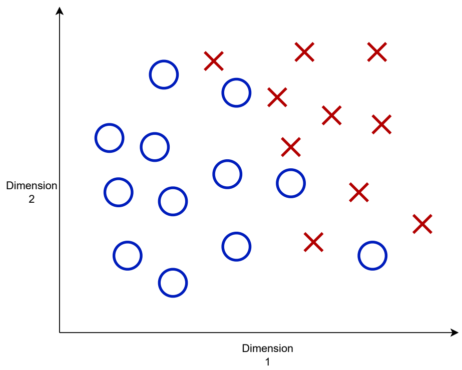

Fig. 4 Training set for KNN.

When classifying a new unknown datapoint, the Euclidean distance from the new datapoint to all existing points is calculated. The k neighbors with the shortest distance are then used to determine the class of the new datapoint. The value of k is user-defined and determines how many of the closest neighbors are considered for classification. The class of the new datapoint is determined based on the classes of the k nearest points. In an unweighted classifier, the class that is most represented among the k neighbors is chosen as the class for the new datapoint. However, weights can be assigned to the distances to modify the model. A weight can be a function of distance, where points closer to the new datapoint contribute more to the average class than more distant ones. In Figure 5, an unknown datapoint without a class has been applied to the model in Figure 4. The class can be determined using an unweighted KNN with a k value of three. Therefore, the classes of the three nearest points are examined. If there are two crosses and one circle among the three nearest points, the new datapoint would be classified as a cross [5].

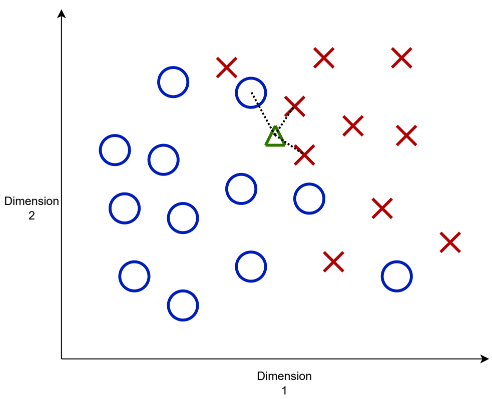

Fig. 5 KNN with a new datapoint for classification.

2.4 Linear Discriminant Analysis

Linear Discriminant Analysis is a dimensionality reduction algorithm designed for high-dimensional data. In this project, LDA was tested because the KNN algorithm had a long classification time, and as close to real-time classification as possible was desired. LDA aims to reduce the dimensions of the data while maximizing the separation between classes. Figure 6 illustrates a comparison between LDA and the unsupervised algorithm Principal Component Analysis (PCA). It demonstrates how LDA strives to separate the classes as much as possible during dimensionality reduction. The algorithm performs the most computationally intensive tasks when optimizing the dimensionality reduction to maximize class separation during training. Additionally, it should be noted that the LDA model stores training data but only retains information about how the data should be transformed. As a result, the LDA model is significantly lighter in terms of computational requirements during classification compared to the previously described KNN model [5].

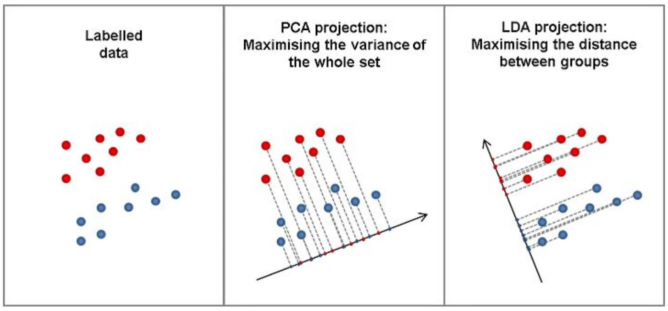

Fig. 6 Comparison of dimensionality reduction algorithms [6].

2.5 Solution Approach

The complexity level of the solution will change based on the automation level. It will be difficult to implement a fully automatic solution in one step. A proposal for the steps for implementing automatic solutions at LF is illustrated in Figure 7.

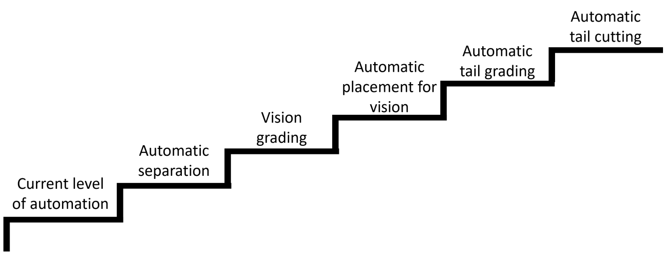

Fig. 7 Innovation staircase.

3. Vision (VT3.025-5)

3.1 Detection of Spoilage (VT3.025-5)

Rotten scampi are the biggest priority for LF, as there would be the highest risk of critical customer complaints if a spoiled scampi was packaged. Furthermore can customers become sick if a spoiled scampi is consumed. Therefore, the first priority will be detection of spoilage in the scampi at LF. Initially, the goal will be to prove, whether or not Hyperspectral Imaging (HSI) can be used for measuring the spoilage in scampi. The result of this test will then define the further development, and whether or not other technologies must be investigated.

3.2 Initial Validation of Hyperspectral Technology (VT3.025-5)

SPKTRA, a company specializing in HSI of various food products, including seafood, has developed a HSI camera and a sealed lighting environment consisting of a black box with controlled lighting equipment. The halogen lamps used in the setup emit a broad spectrum of light, including infrared and ultraviolet light, which are essential for HSI. The HSI camera is mounted in the top of the box. The image acquisition box is shown in Figure 8. To minimize reflection, the scampi were placed on a tray covered with non reflective black tape. The camera has a snapshot type sensor, which means that all data in the image is acquired at once, and no scanning of the scampi is necessary. The camera has a spatial resolution of 263x268 pixels and a spectral resolution of 423 bands ranging from 423 nm to 910 nm.

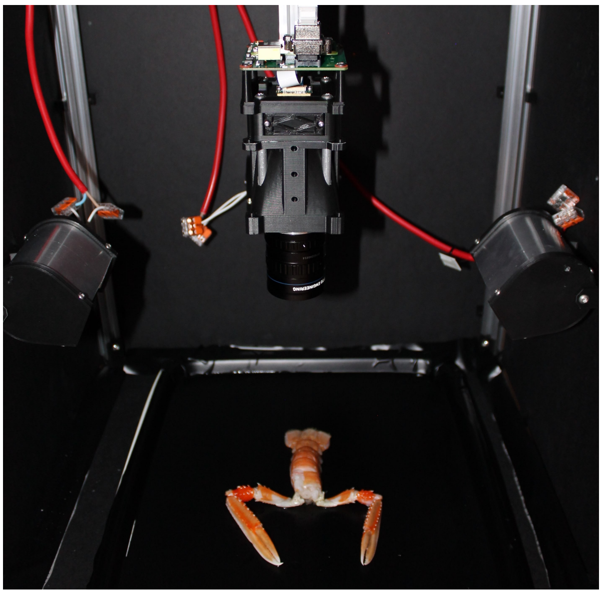

Fig. 8 Inside of Image Acquisition Box.

SPKTRA has developed a user interface for capturing and viewing images taken with the camera. The user interface is shown in Figure 9, where two images can be seen side by side. Additionally, a graph showing the wavelengths in the selected pixels (indicated by the red dot) for both images is displayed. The graph highlights the difference between the two images with a red line.

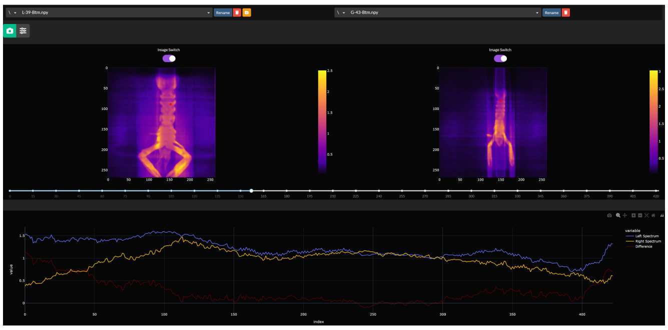

Fig. 9 Result of test 1.

The first part of the validation test is performed by comparing a fresh scampi and a spoiled scampi, as shown in Figure 9. The graph shows a significant difference in the two outside the visible spectrum of light. The second part of the validation test is performed by leaving a scampi in the box for several hours to examine the spoilage that develops over time. The results of the experiment showed that the graph changes although nothing in the setup has changed, as shown in Figure 10. This could mean that the HSI camera is able to detect the level of spoilage in the inspected scampi. This could prove that a machine learning model has the potential to be utilized to classify the scampi as fresh or spoiled using the HSI technology.

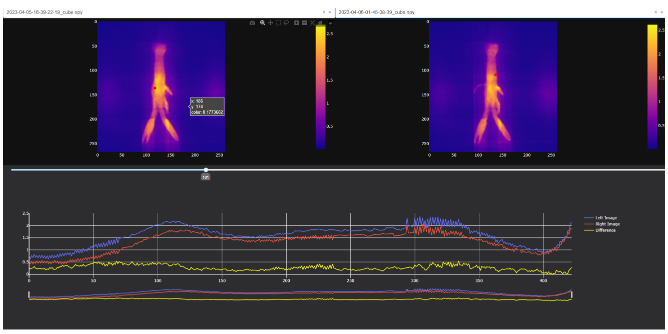

Fig. 10 Difference in spectrum of a scampi after nine hours at room temperature.

3.3 Required Processes

After the initial validation tests, it has become clear that certain processes need to be performed before and after utilizing HSI technology. These processes are illustrated in Figure 11. There are two types of processes: physical intervention and vision inspection. Group 3.025-5 will focus on developing only the vision-based processes, while the processes requiring physical intervention will be developed in a mechanical solution by Group 3.025-6.

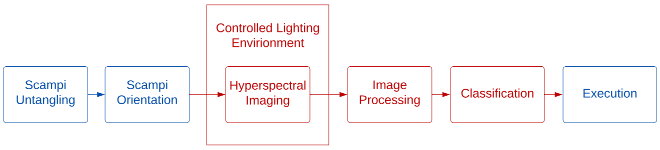

Fig. 11 Required processes in the concept. BLUE: Physical intervention. RED: Vision inspection.

3.3.1 Scampi Untangling

Scampi that are transported in boxes and later transferred to thawing tubs often become entangled during transportation. Therefore, it is important that the scampi are untangled so that only one scampi is in the image at the time for inspection using the vision system. The process of untangling scampi can be a time-consuming and labor-intensive task when performed manually, so this could benefit from automation. One way to automate this process is by using a mechanical system that separates the scampi one by one before they are transported to the next step in the process.

3.3.2 Scampi Orientation

In order to gather comprehensive information about the scampi through the vision system, it is crucial to inspect both the top and bottom surfaces. This is because certain defects such as cracked shells, missing eyes, and ruptured roe in the head are only visible from the top, while sand and dark coloration are primarily visible from the bottom.

By examining both surfaces, the vision system can capture and analyze the relevant details of the scampi. Therefore, it is necessary to properly orient the scampi for both top and bottom inspection. This process could also benefit from automation, and the scampi could be oriented using a mechanical system that positions each scampi in a predetermined way before it is inspected. This ensures that the scampi are properly inspected, improving the accuracy of the classification.

3.3.3 Hyperspectral Imaging (VT3.025-5)

Once the scampi has been oriented, the HSI camera captures an image, and the relevant information from the scampi needs to be extracted. To achieve this, the image is acquired within a controlled lighting environment, where the lighting remains constant and unaffected by ambient light. This ensures that the captured information pertains solely to the scampi. Furthermore, it is important to note that the resolution of the HSI camera provided by SPKTRA is lower than that of a traditional camera. Therefore, it is currently uncertain whether it is adequate for detecting all of the additional criteria. However, this will not be investigated in this paper.

3.3.4 Image Processing (VT3.025-5)

Image processing plays a crucial role in computer vision to analyze the images captured by the HSI camera and extract valuable information about the scampi. Once the image is acquired, it undergoes a series of processing steps to enable classification and further analysis. These steps involve employing different image processing techniques, such as segmentation of the scampi from the background, as well as spectral analysis of the images captured by the camera. This spectral analysis can be performed on the entire scampi or specific parts of it. The main objective of image processing is to effectively extract the necessary information that can be utilized for subsequent classification tasks.

3.3.5 Classification (VT3.025-5)

After the image processing is complete, the scampi can be classified based on a supervised data set that includes examples of both fresh and spoiled scampi. Various classification methods can be employed, utilizing the known training images to determine whether the scampi in the testing images are approved or denied.

3.3.6 Execution (VT3.025-5)

Once a scampi has been classified, it must be sorted accordingly. This process can also benefit from automation, and a mechanical system could be developed to sort the scampi after classification. Therefore, the vision solution must communicate to the mechanical solution about what to do with the inspected scampi. However, the communication between the two solutions will not be developed in this paper.

3.3.7 Testing (VT3.025-5)

It is crucial to collect as much data as possible to create a robust machine learning model for classifying scampi. This is achieved by visiting LF and hand-picking scampi related to the two categories chosen in the concept (spoilage & missing claws). During the visit, 60 fresh and 60 spoiled scampi were collected, with a mix of none, one, or both claws missing. These samples are also included in the dataset used for training the model on missing claws. Images were acquired of the top and bottom of the scampi using the HSI camera provided by SPKTRA, to determine if there is a preferred side for inspection. By capturing pictures of both sides, the dataset is doubled for both fresh and spoiled scampi, resulting in a total of 240 images. The entire dataset is then split into two categories: a training dataset and a testing dataset.

KNN and LDA were tested for accuracy and execution time. This was accomplished by training the algorithms using the training dataset and using them to classify all testing images. The class of the image was determined based on the number of pixels classified as either good or spoiled. If there was a majority of pixels classified as good compared to spoiled pixels, the image would be classified as a good scampi, and vice versa. The time taken to classify each image was recorded and averaged.

Next, a test was conducted to determine whether spoilage was detectable from both the top and bottom of the scampi or if one side showed more signs than the other. To conduct this test, two models were created: one using images of the top of the scampi for training, and the other using images of the bottom. The models were then tested on corresponding test images with the same orientation of scampi, and the accuracy of the models was recorded.

In the models used for this test, the detection of claws was implemented in order to test if the machine learning models could recognize them. However, no classification accuracy for claws was implemented. The classification accuracy was checked by manually observing the resulting classified images.

3.4 Results (VT3.025-5)

The results of the first test are presented in Table I. It can be observed that the accuracy of the two algorithms is similar, but the classification time for the LDA algorithm is significantly lower compared to KNN. Therefore, the LDA algorithm will be the primary focus from this point onward.

	KNN	LDA
Accuracy	95%	95%
Avg. classification time	80 s	0.4 s

Tab. I Test results on which algorithm would be preferable.

The second test utilized the LDA algorithm, and the results are presented in Table II. The findings indicate that the bottom model was able to correctly classify all images, while the top model achieved a 94% accuracy rate in image classification. Upon examining the classified images, it became apparent that the trained model at the top encountered difficulties with certain images, such as the example shown in Figure 12, where spoilage was detected in a fresh scampi. For comparison, a properly classified scampi is shown in Figure 13. This 6% discrepancy between the two tests may be attributed to the model not being adequately trained for those specific scampi or the presence of imperceptible spoilage in the scampi itself. Notably, across all test models, the same images consistently exhibited incorrect or nearly incorrect classifications.

As can be further seen in Figure 12 and Figure 13, the claws in the images were consistently classified with a yellow color. It was not concluded how many claws were correctly detected, but upon manual examination of the images, the technology proves worthy of being used to detect missing claws.

	Top	Bottom
Accuracy	94%	100%

Tab. II Test results on which orientation would be preferable.

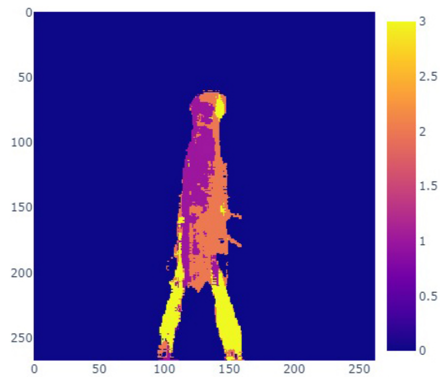

Fig. 12 Good scampi classified as spoiled.

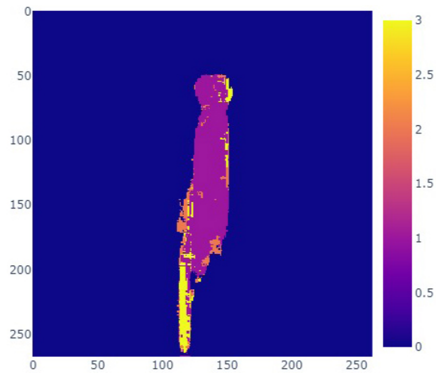

Fig. 13 Good scampi classified correctly.

4. Mechanical Setup (VT3.025-6)

To facilitate the requirements for vision inspection of the scampi, a brainstorm is made to conceptualize possible solutions.

4.1 Principle Development (VT3.025-6)

The purpose of the brainstorming session is to broaden the range of possible solutions and generate ideas for a concept. It specifically aims to generate ideas that facilitate the untangling and separation of the scampi, while also ensuring their proper positioning for easy pickup by the worker and placement on a conveyor for transportation to the vision inspection area.

4.2 Test of Principles (VT3.025-6)

Four principles derived from the problem analysis and brainstorming have been selected for testing.

- **Vibration:** Has the potential to untangle the scampi [7].
- **Conveyor Acceleration:** Acceleration on conveyors to increase space between the scampi [8].
- **Water:** Examine behavior of a pile of different sized scampi in water [8].
- **Brushes:** Separation of scampi on conveyor.

The goal for the solution is to untangle and separate the scampi. The listed principles will be evaluated from one to five with respect to the following parameters to determine their potency for implementation:

- **Untangling:** Ability for the concept to untangle scampi.
- **Singulation:** Ability to isolate or align the scampi.
- **Compactness:** How much physical space is needed for the concept.
- **Complexity:** How many components and calibration is required for the concept to work properly.

The principles evaluation within each of the parameters is used to develop a concept that fits into an already existing production and fulfills the task of separating the scampi.

4.3 Concept Development (VT3.025-6)

Relying on a single principle may not suffice to effectively address the task at hand. It is necessary to take into account the combination of principles in order to find a comprehensive solution. Additionally, it is important to keep in mind that the concept should be developed with future automation possibilities in consideration.

To keep a broad design space, multiple concepts with different combinations of principles have been examined. In order to compare these concepts to one another, an evaluation of each concept from one to five with respect to the following parameters has been conducted:

- **Reliability:** How well the concept handles objects that are expected.
- **Robustness:** How well the system handles unexpected foreign objects.
- **Versatility:** How well the solution can be used for other tasks than what it is designed for.
- **Scalability:** How well the concept can be scaled to increase capacity.
- **Noise level:** How high a noise level the concept is expected to have.
- **Interoperability:** The ability for the concepts to work with the existing processing equipment at LF.
- **Complexity:** How complex the solution is, based on the concepts used as well as how many are incorporated.

4.3.1 Chosen concept (VT3.025-6)

Based on the evaluations of the different concepts, the best scoring concept has been chosen. This concept is sketched in Figure 14. The concept makes use of the principles **water**, **vibration** and **conveyor acceleration**. To accommodate the need for short term wins, a step wise implementation of concept is proposed, which is why the concept has been designed for manual work with later automation implementation in mind.

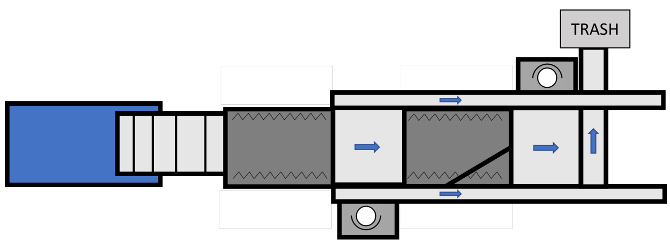

Fig. 14 Best scoring concept.

4.4 Final Solution (VT3.025-6)

The final solution has been determined in case of design and necessay metrics based on the chosen concept. An illustration of the final solution is in Figure 15. The solution will be just short of six meters in length and 1.2 meters in width. The velocity for both the vibration tables are determined to be $0.25\,\mathrm{m/s}$ and for the picking conveyors $0.3\,\mathrm{m/s}$. The velocities are calculated to maintain the current production output while still give the workers time to handle the scampi. While the scampi are placed in the longitudinal direction with respect to the conveyors leading to the vision station, the velocity needs to be higher. For these conveyors it is calcualted to be $0.5\,\mathrm{m/s}$ to maintain production output.

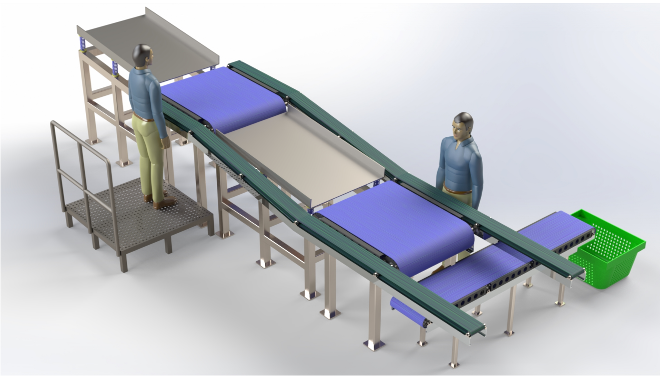

Fig. 15 Final design of solution.

4.5 Implementation and Performance (VT3.025-6)

Proposals have been suggested for how the final solution should be implemented at the facility in Skagen. A priority has been to maintain the production capacity throughout the transition. Steps for gradual implementation have been proposed to achieve this, and the first implementation step is illustrated in Figure 16. The vibration table and an automatic vision inspection have been implemented to fit with the existing infrastructure at the facility in Skagen. At this step, three workers will do normal manual quality sorting, and one worker will orient the scampi to be inspected by the vision and hyperspectral technology.

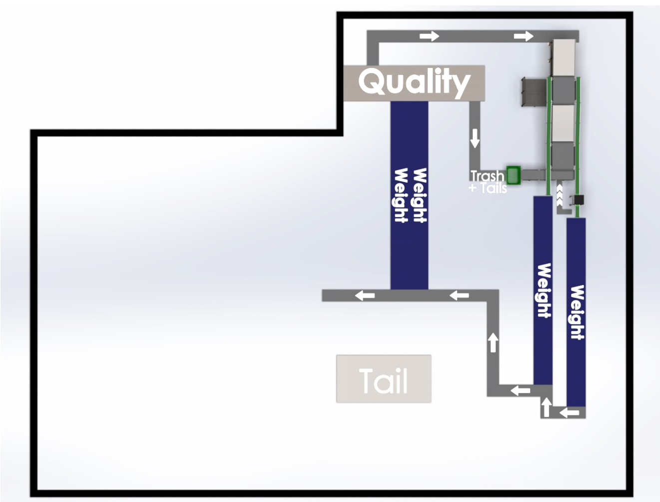

Fig. 16 Suggested first implementation step at LF.

Three subsequent implementation steps follow, until the facility has been fully reconfigured for an automated quality inspection in step 4. After implementing the last step, the production will have two of the solutions from Figure 15, four delta robots guided by vision cameras to grasp the scampi on the picking conveyor, and four vision boxes with HSI camera and controlled lighting for the quality inspection. Conveyors will transport the quality inspected scampi to be automatically weight graded.

Both a Value Stream Map and Discrete Event Simulation have been made for the current production, implementation step 1, and implementation step 4 in order to conclude on the performance of the automatic solution and the steps toward achieving it. The most important metrics have been extracted for the current production, step 1, and step 4 and compiled in Table III.

	Current	Step 1	Step 4
Max Capacity (Scampi/minute)	300-360	360-420	340
Daily Capacity (Packages)	6058	6684	6537
Number of Workers	3	4	-
Number of Vision Boxes	-	1	4
Number of Delta Robots	-	-	4

Tab. III Comparison of the current setup, implementation step 1, and implementation step 4

The current production setup utilizes manual labor, which varies in efficiency based on the capabilities and skill-level of the individual worker. This results in a varying output. An automatic quality sorting will contribute to a stable output and a longer production time, both on daily and weekly basis. Manual workers will require breaks and days free during the week. This is a challenge on weeks where the fishermen have caught a lot of scampi, and a longer production time is required.

4.6 Risk Assessment and Investment

A risk assessment is made to conclude on the financial feasibility of an automated quality sorting.

4.6.1 Using SPKTRA HSI cameras (VT3.025-6)

While an automatic quality sorting will result in benefits for LF, it must also be financially feasible. The total cost consists of development cost, implementation cost, and operation cost. SPKTRA has provided a prices for the camera solution:

- 300,000 DKK for the first month.
- 240,000 DKK for the second month.

- 27,000 DKK monthly after implementation.

Taken into account the SPKTRA prices, prices for developing, and implementing the mechanical system, Figure 17 is made. The prices are inserted as ranges to accommodate for uncertainties. The automated quality sorting is implemented in the previously described steps, which are marked with vertical lines. The current production expenses using manual labor has been plotted to estimate a pay-back time.

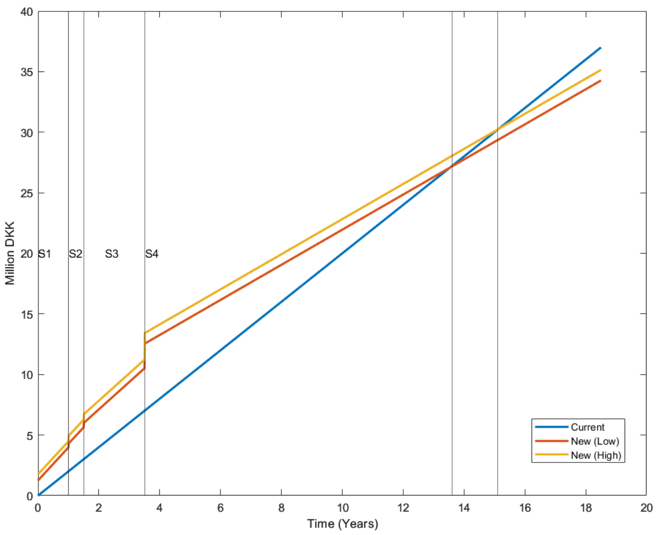

Fig. 17 Graph for current expenses vs expenses implementing the automatic quality sorting using SPKTRA cameras.

The figure suggests a pay-back time of 14-15 years. This is deemed financially non-feasible, and the recommendation for LF will be to wait on the investment, if SPKTRA cameras are used.

4.6.2 Local Computing Solution (VT3.025-5)

A local computing solution conecpt has been designed, in order to attempt to eliminate the limitations of the solution which utilized hardware and software from SPKTRA. The system is using two line-scan cameras. These cameras are positioned in a slit on the conveyor, combined with a small descent, the scampi travel past, jumping a gap. One camera is placed below the conveyor, looking through the slit and scanning the bottom of the scampi, while the other camera is placed on top of the conveyor, scanning the top of the scampi. This configuration is illustrated in Figure 18. To ensure a controlled lighting environment, lamps will be mounted at a 45-degree angle to the camera, illuminating the scampi. Additionally, shielding would be implemented around the camera and light setup to block any unwanted ambient light.

Due to LF currently requiring three conveyors to achieve a capacity of 360 scampi per minute, it has been determined that two quality control conveyors are needed. These conveyors would be wider than the current ones, allowing for two scampi to be transported side by side, thereby reducing the number of cameras required. Therefore, a total of four cameras and four lamps are needed.

The mechanical solution will be similar to the one presented in subsection 4.4, but modified for the new vision system. As a result, the price estimation for the mechanical part of the solution will remain the same. The solution will utilize four Specim FX10 [9] cameras due to their high image acquisition rate, which is necessary when handling a capacity of 340 scampi per minute. The lighting setup will consist of four UL-Style Line Light LED bars from Metaphase Technologies [10] as they meet the wavelength requirements of the Specim cameras. This solution requires software developed specifically for classifying scampi. An estimated price on software has been provided by a third party. A summary of the pricing is present below:

- [4 pcs] Specim FX10 cameras [9].
  - ❏ €56 000 (418 000 DKK).
- [4 pcs] UL-Style Line Lights from Metaphase Technologies [10].
  - ❏ €34 528 (258 000 DKK).
- Mechanical solution developed by Group 3.025-6 modified to new requirements.
  - ❏ 2 000 000 DKK.
- Specialized software solution.
  - ❏ 1 364 000 DKK.
- One worker who supervises the automatic system.
  - ❏ 400 000 DKK per year.

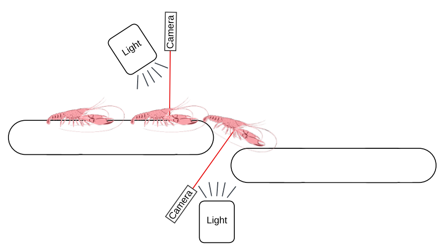

Fig. 18 Illustration of the camera and light configuration on the developed solution.

4.7 Comparison of Solutions

In Figure 19, the total cost over time for the SPKTRA solution at step four, the local solution and the current configuration is visualized. Here, it can be seen that the solution with SPKTRA has a small initial investment of 2 333 000 DKK and a monthly cost higher than that of the current processing setup. This implies that the overall cost will be higher than that of the current setup. The point of discussion is whether or not the higher investment needed for this solution would be worth the problem presented of not being able to find new employees when the current workforce essentially quits. LF would have to accept this compromise if this solution were to be implemented.

The localized computing solution presented shows a requirement of a larger initial investment of 4 000 000 DKK, as both mechanical equipment and vision equipment have to be purchased. However, the running cost is shown to be substantially lower than both the SPKTRA solution and the current solution, leading to a payback time of four years and eleven months compared to the current solution. The solution also proves to be cheaper than the SPKTRA solution after one year and three months, considering the higher initial investment.

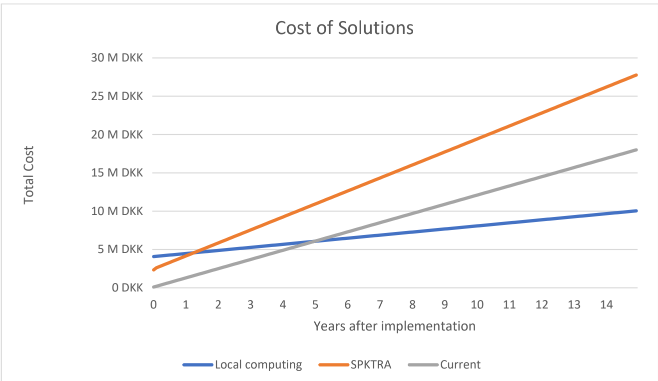

Fig. 19 Total cost of the different solutions and the current manual quality inspection.

5. Conclusion

This paper has shown work constructing a system consisting of mechanical and computer vision parts. The computer vision part has shown great progress in utilizing machine learning and hyperspectral imaging for detecting spoilage in scampi.

A mechanical system has been designed to untangle, separate, and orient the scampi for the vision inspection. A solution using vibration tables and accelerating conveyors has been chosen. A stepwise implementation has been established to ensure that the capacity is maintained.

Based on results from the utilization of HSI technology to quality sort scampi and the mechanical setup facilitating the vision inspection, two investment scenarios have been established: One based on SPKTRA technology, and one based on local computing equipment and industrial grade camera and lighting hardware.

The solution utilizing SPKTRA technology proved to not be financially feasible compared to the solution using local computing equipment and industrial grade camera and lighting hardware.

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