Automated Vision System for Cutting Fixed-weight or Fixed-length Frozen Fish Portions

Dibet Garcia Gonzalez[1], Nelson Alves[1], Ricardo Figueiredo[2], Pedro Maia[3] and Miguel Angel Guevara Lopez[1,4]

[1]*Computer Center Graphics, Minho University, Guimarães, Portugal*

[2]*Gel Peixe, Loures, Portugal*

[3]*Sociedade Industrial de Robótica e Controlo, S. A., Aveiro, Portugal*

[4]*Centro Algoritmi, Minho University, Guimarães, Portugal*

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Abstract: The increase in fish demand poses a challenge to the food industry that needs upgrades both for: (1) offering new and diverse products and (2) optimizing it's processing line throughput and at the same time guaranteeing the fishes' quality and appearance. This work presents an innovative computer vision system, to be integrated into an automatic frozen fish cutting production line. The proposed system is able to perform the 3D reconstruction in real time of every frozen fish, and allows to: (1) identify and automatically separate head bone, body and tail parts of the fishes; and (2) estimate with high accuracy where cut the fishes' body to produce the wanted slices, according to requirements (parameters) of weight or width previously defined. The experimental and statistical results are very promising and show the viability of the developed system. As main contribution (novelty) this new method is able to estimate automatically and with high precision the weight of the part corresponding to the body of the fishes and thus optimizing the cut of the fish slices. With this, we expect to achieve a significant reduction of fish losses.

1 INTRODUCTION

Fishing is one of the sources of food, nutrition, financial income and livelihoods for hundreds of millions of people around the world. The supply of fish at worldwide level reached a record high of 20kg per capita in 2014 (Food and of the United Nations, 2016). This increase in fish demand poses a challenge to the industry whose current approaches for fish cutting are mainly based on manual work and cuts are made using only fixed dimensions. On the other hand, consumers want to buy fish by weight, without scales and with a great visual appearance (freshness). This demand, imposes a challenge to the food industry that needs upgrades both for: (1) offering new and diverse products and (2) optimizing it's processing line throughput and at the same time guaranteeing the fishes' quality and appearance.

Currently, food processing, as it is the case of fish, tends to be carried out in industrial and automated environments (Booman et al., 2010). Currently, automation is more and more a reality due to the well known advantages. The Automatic (Automated) Optical Inspection (AOI) algorithms and methods are currently part of the "automation" bundle and allows for precision, repeatability, and uninterrupted periods of work during all the year.

This work presents a new computer vision system, to be integrated into an automated processing line, able to the three dimensional (3D) reconstruction of frozen fish (in real time), and automatically segment the fishes into three (defined) parts (i.e. head bone, body and tail). Also, the developed system will estimate with high accuracy where (attending to an established reference coordinate system) to cut the fishes slices according to requirements (parameters) such as weight or width.

The AOI-based method proposed here is a tailor-made solution developed for a specific client, a representative player of the Portuguese and international fish industry. This new system will allow to optimize the cutting process, replacing the today current scenario where a human operator is responsible for cutting the frozen fish in a pre-determined and fixed di-

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mension while at the same time inspects it for "defects" (e.g. if it is the "head bone" present and visible?).

2 PREVIOUS WORK

The computer vision technologies applied to the industry cover a great variety of solutions for image acquisition like: visible/near-infrared, computed tomography, X-ray (Kelkar et al., 2015), magnetic resonance imaging, laser scanner (Kelkar et al., 2011) in 2D and 3D space (Mathiassen et al., 2011). The estimation of weight using computer vision techniques implies the determination of density. Magnetic resonance imaging, computed tomography, laser scanners,and even X-ray are imaging modalities that have been frequently employed for this kind of task.

An overview of some of the AOI-based developed solutions for "food inspection", in specific, focused to compute (estimate) parameters, such as the weight and density are presented to follow.

In (Viazzi et al., 2015), computer vision techniques are used to estimate the weight of a complete fish. The study uses regression techniques to find the best model that estimates weight using features extracted from images. The computer vision algorithm includes four steps. First, detect the region that encloses the fish. Second, the fish is segmented using the "Otsu adaptive thresholding" algorithm. Next, it is removed the tail fin using a shape analysis method. Finally, some features like height, length, and area are extracted with and without including the tail fin. As conclusions, authors state both for: 1) the area parameter is sufficient and more robust to estimate the weight of a fish; and 2) the tail fin negatively influences the weight estimation. Another approach tries to establish a relation between the projected area of sushi shrimp, captured using an RGB camera, and its corresponding weight (Poonnoy and Chum-in, 2012).

In (Mortensen et al., 2016) for the use case of broiler chickens weight estimation, it is described a system composed of a weighing platform (used to give a reference weight) and a RGB-D sensor (Microsoft kinect), where authors developed an algorithm including the following steps: (1) segment the broilers using watershed and region growing techniques in a previously filtered gray-scale image (combining a Gaussian filter and morphological operators); (2) the extraction of features like projected area, width, perimeter, radius eccentricity, volume and others from each segmented broiler; and (3) weight prediction of each broiler based on the extracted features using artificial neural networks. A convex hull and numerical integration are used to obtain an approximated 3D model of the broilers.

In (Adamczak et al., 2018) it is used a white light (3D scanning) technology to determine the weight of the chicken breasts.

Eggs volume estimation based on computer vision techniques was explored by (Soltani et al., 2015) with the objective to extract the eggs major and minor diameters. Two methods for estimating the volume were tested: 1) a Mathematical model based on Pappus theorem; and 2) Artificial Neural Networks. As result, it was observed that the developed mathematical model achieved better results..

3 AUTOMATIC VISION SYSTEM

In order to support the development of the proposed method, we built an experimental prototype (a stand alone machine) comprising: 1) a conveyor belt that moves at a speed of 0.5 m/s, which can transport fishes of different sizes and volumes; 2) a precision scale; 3) two "Entry-Level 3D Laser Line Profile Sensors" - Gocators 2150 (Technologies, 2018) in an opposite layout placed at a distance of one meter (Figure 1). The Gocator 2150 is a 3D smart sensor / camera, an all-in-one solution that lets factories to improve efficiency in product validation; and 4) an industrial PC.

With this, each fish is weighted using the scale and its total weight (T_w) is recorded. Then, the fish is scanned using the Gocators sensors, resulting two line profiles (corresponding to both sides of the fish; top and bottom). The computed profiles are then integrated generating a precise 3D fish model using a fine tuning developed computer vision algorithm.

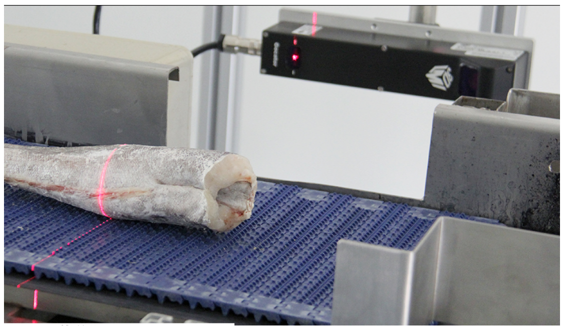


Figure 1: Hardware prototype of the acquisition module, including sensors that emits and capture lines of laser that are projected in the fish body over the conveyor belt.

Taking as input the generated 3D model, we estimate the individual weight of a voxel (V_w) dividing the total weigh of the fish (T_W) by the total number of the computed voxels. A voxel is considered the minimum unit of a 3D object (the fish in this case) with dimensions w, l and h respectively. Additionally, it is computed the total volume (T_V) as the sum of all the volumes of the voxels. The fish density (ρ) is calculated dividing the total volume (T_V) by the total weight(T_W).

The cameras reference system is used as the global coordinates system. Therefore, the two produced profiles are identified as the top and the bottom respectively. The x axis coincides with the width (w), the z axis with the height (h) and the y axis with the length (l) of the fish.

The built 3D model is then segmented in three parts: the head bone, body and tail fin models. The head bone is considered waste and body and tail fin are separated to be processed before introducing these into the cutting system machine. In the next step, the 3D model of the body part is used as input to determine the optimal coordinates of slices for each individual fish, taking into account the previously selected parameters (length or weight). The description of the mechanical part of the cutting system machine will not be discussed here, due to, it is not an objective of this work.

3.1 Data Acquisition and Pre-processing

For the development of this work, we used an example dataset comprising 200 fishes of Merluccius merluccius with different sizes, supply by the "Gel Peixe" company (http://gelpeixe.pt). The used sensors / cameras (Gocator 2150) capture information such as: intensity levels and depth profiles. However, we used only, as input data, the top and bottom depth profiles captured by the sensors, which are acquired when the fishes are moving through the conveyor belt, inside of the sensors field of view (the y axis). Cameras are previously calibrated and aligned, guaranteeing that the extrinsic parameters between both cameras are known. An encoder is used to trigger the cameras in a synchronized way. With this, we have a resolution that allows to capture voxels with the following dimensions in mm: $1x1x0.6$ (x,y,z) respectively.

The pre-processing step aims to remove every information that is not belong to the fish, such as the foreign objects and the conveyor belt among others.

The foreign' objects subtraction consists in the application of a thresholding process to both profiles (top and bottom) in which are correlated the width of the conveyor belt and the maximum width of the fish. The threshold was selected heuristically taking into account the fish dimensions. It allows the selection of a correct ROI (Region of Interest), which is critical for the execution of the next steps. The Figure 2 shows the measured profile from each camera and the manual threshold selection.

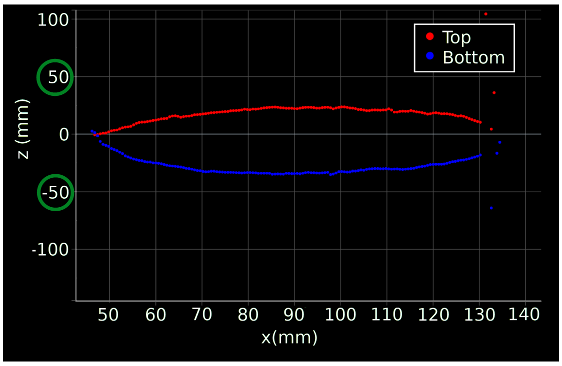
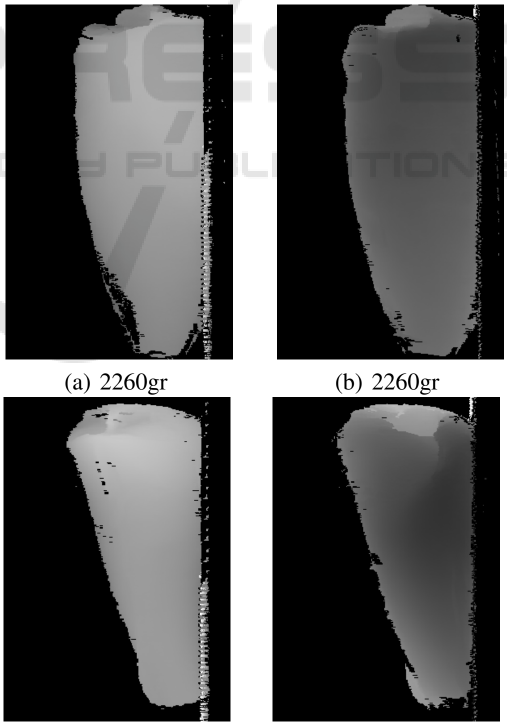


Figure 2: Example of profiles: Top (red) and Bottom (blue). Heuristically selected thresholds (enclosed in green circles).

While the fish is crossing the field of view of the cameras, the profiles are captured and stored in order to form two gray-scale images (Figure 3). These images still need a filtering step in order to remove the conveyor belt and other noise related to the profile acquisition.



(a) 2260gr (b) 2260gr

(c) 1880gr (d) 1880gr

Figure 3: Bottom (a, c) and top (b, d) images without the filtering step

For this task, we employ mathematical morphology operators combined with logical operations, as presented to follow. These steps are applied to the bottom (f_b) and top (f_t) two dimensional (2D) gray-scale images.

1. Adjust the coordinate system.

$$f_t(x,y) = f_t(x,y) + \min(f_b(x,y)) \quad (1)$$

$$f_b(x,y) = f_b(x,y) + \min(f_b(x,y)) \quad (2)$$

   where $\min(f_b(x,y))$ calculates the minimum (coordinates in the z axis) value of the bottom profile.

2. Image binarization

$$b_t(x,y) = \begin{cases} 1 & \text{if } f_t(x,y) \neq 0 \\ 0 & \text{if } f_t(x,y) = 0 \end{cases} \quad (3)$$

$$b_b(x,y) = \begin{cases} 1 & \text{if } f_b(x,y) \neq 0 \\ 0 & \text{if } f_b(x,y) = 0 \end{cases} \quad (4)$$

3. Binary mask

$$m(x,y) = b_t(x,y) \vee b_b(x,y) \quad (5)$$

4. Improving the binary mask. It is applied a morphological opening operation with structuring element K to $m(x,y)$, with this are removed small (noise) particles.

$$m(x,y) = (m(x,y) \ominus K(a,b)) \oplus K(a,b) \quad (6)$$

5. Gray image reconstruction

$$f_t^{'}(x,y) = f_t(x,y) \times m(x,y) \quad (7)$$

$$f_b^{'}(x,y) = f_b(x,y) \times m(x,y) \quad (8)$$

6. Blob (fish) detection and image cropping. In this step we find the regions of interest (the fish) in $f_t^{'}$ and $f_b^{'}$. Then, the bounding boxes (rectangles) that enclose each blob are superimposed in order to form a new rectangle that is used in the cropping process of $f_t^{'}$ and $f_b^{'}$. An example can be seen in Figure 4.

7. A Gaussian filtering is applied to reduce noise, which allows to smooth the previously reconstructed gray image.

The Figure 5 shows the image evolution since step 1 to step 7.

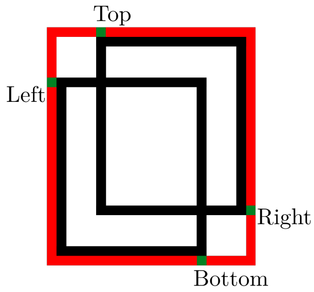


Figure 4: Rectangle estimation used in the cropping process of $f_t^{'}$ and $f_b^{'}$.

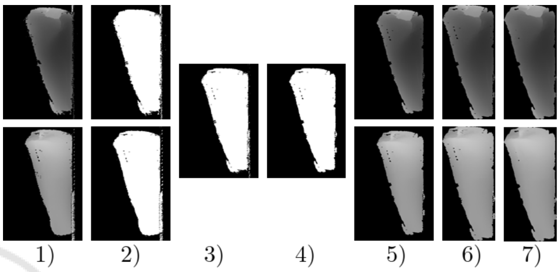


Figure 5: Image processing work flow (steps).

3.2 3D Model Reconstruction and Density Estimation

The filtered top and bottom images are used as input to build the 3D model. The corresponding row in both images are used in the building of L new images containing the edges (contours) of the region (area) of the fish in each particular image (plane) (see Figure 6). Unconnected points are linked using a cubic spline algorithm to close the fish area in each plane. The number of pixels enclosed by this area is $N_{i=1..L}$. The total area (in mm^2) is calculated using the equation:

$$A_{i=1..L} = N_i * w * h \quad (9)$$

The volume in mm^3 between two continuous images planes is computed as:

$$V_{i=1..L} = A_i * l \quad (10)$$

The total fish volume (T_V) in mm^3 is:

$$T_V = \sum_{i=1..L} V_i \quad (11)$$

Knowing the weight (T_w) of each fish and its volume (T_V) we can estimate its density ρ as:

$$\rho = \frac{T_w}{T_V} \quad (12)$$

Finally, is calculated the weight associated to the i_{th} image as:

$$W_{i=1..L} = V_i * \rho \tag{13}$$

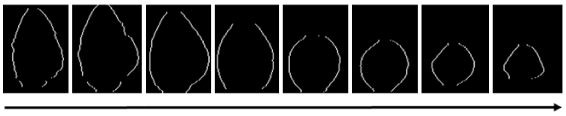


Figure 6: Profile samples.

3.3 Fish Segmentation

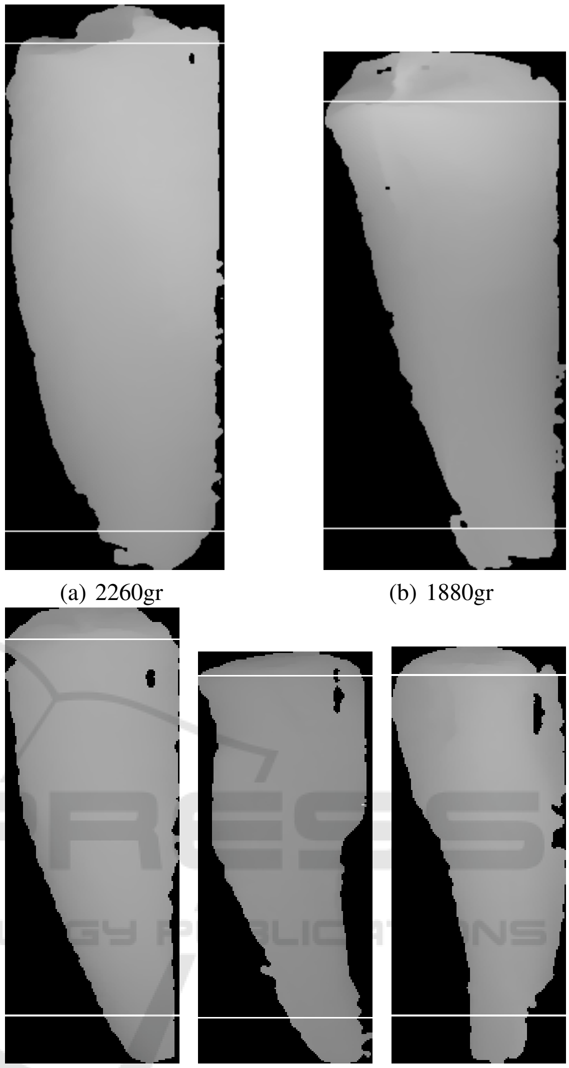
The cutting process of frozen fish always involves a first stage of bone cutting (i.e. the head bone). The detection of the exact position where to cut the head bone (L_{bone}) is a trial and error process when done manually. An experienced operator can make 2 to 3 cuts on the same fish before to achieve a first slice of the fish with the expected (optimal) quality. To extract the correct place (position) for cutting the head bone, we developed a simple algorithm that takes as input the images obtained in the step 7, as it can be observed in the sub-section 3.1 (see Figure 5).

To automatically identifies the coordinates for cutting the head bone, we developed an algorithm that consists in moving a segment of line using an inclination angle of 30° from the upper left edge downwards in both images (top and bottom). This procedure is repeated until (at least) the segment of line intersect one of the pixels belonging to the fish, in any one of the two images (top or bottom). The length of the tail fin (L_{tail}) depends on the size of the fish and the optimization strategies (i.e. the length that was previously defined by the costumer). With this, the body (L_u) is considered the part (portion) between head bone and tail fin (space between L_{bone} and L_{tail}, which is the "useful space" for cutting the slices of the fish. The Figure 7 shows two segment of lines, which identified (divide) the head bone, body and the tail fin section of the fish.

3.4 Fish Cut Optimization Strategies

Once segmented the body of the fish, the next step is related to computing the coordinates where its will be produced the cuts for obtaining the optimized fish slices. As required by the costumer, the fish can be processed following one of two well-defined strategies: 1) Fixed-Length, using as input a selected length, between a range of values to cut the fish slices; and 2) Fixed-Weight, using as input a selected weight to cut the fish slices.

The Fixed-Length strategy allows a length range between min_{length} and max_{length} to apply the cuts.The



(a) 2260gr (b) 1880gr

(c) 670gr (d) 520gr (e) 510gr

Figure 7: Bone estimation and tail fin section. The tail length is fixed to 3cm.

goal is to minimize the waste, therefore, it can be intended as the minimization of the distance between the last slice coordinates and the start-off position of the tail fin (L_{tail}). For this purpose, we use the algorithm 1. In our setup, we consider the size of the fish as having L mm, due to the fish's profiles coordinates are acquired with a distance of 1 mm in the sense of the y axis.

The algorithm 2 describes the Fixed-Weight strategy.

Algorithm 1: Fixed-Length strategy algorithm. The IF condition allows adding $1mm$ more in another to consider the loss produced by the saw.

Result: A vector with all the cuts positions $(positions)$
$L_u = L - L_{bone} - L_{tail}$;
$cuts\_number = 0$;
$rest\_space = L_u - cuts\_number * min\_length$;
while $(rest\_space > max\_length)$ **do**
  $cuts\_number++$;
  $rest\_space = L_u - cuts\_number * min\_length$;
end
$adding = rest\_space / cuts\_number$;
$real\_cut\_width = min\_length + adding$;
$start = L_{bone}$;
$positions = []$;
for $(i = 0; i < cuts\_number; i++)$ **do**
  $position\_to\_add = 0$;
  if $(real\_cut\_width + 1 > max\_length$ **then**
    $position\_to\_add = max\_length$;
  else
    $position\_to\_add = real\_cut\_width + 1$;
  end
  Insert $position\_to\_add$ into the vector $positions$;
  $start += position\_to\_add$;
end

Algorithm 2: Fixed-Weight strategy algorithm.

Result: A vector with all the cuts positions $(positions)$
$start = L_{bone}$;
$acc\_weight = 0.0$;
$positions = []$;
for $(i = L_{bone}; i < L_{bone} + L_u; i++)$ **do**
  $acc\_weight += V_i * \rho$;
  if $(acc\_weight >= desired\_weight)$ **then**
    $position\_to\_add = i - start$;
    Insert $position\_to\_add$ into the vector $positions$;
    $start = i$;
    $acc\_weight = 0.0$;
  end
end

4 EXPERIMENTAL SETUP / VALIDATION

In order to validate and verify the developed methods, we use the Merluccius merluccius dataset, a set of fishes (with different weights), which were continuously scanned, and volume of every fish in each iteration was computed. Then, statistical descriptors, such as, the mean and standard deviation were extracted. An example, using one fish can be observed at Figure 8, which shows the volume profiles of a fish (weighting $1880gr$) computed 200 times in different positions, using the Equation 10. The Table 1 shows the statistical descriptors (mean and standard deviation) computed 200 times in different positions using five different fishes.

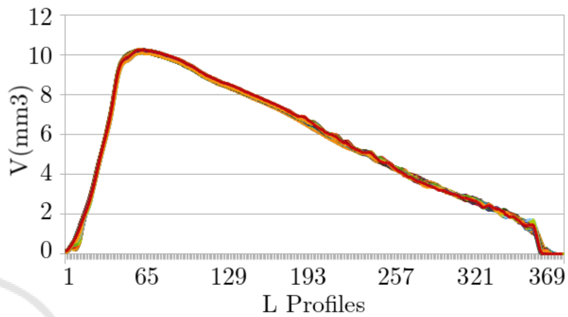


Figure 8: Volume behavior after scanning a 1880 gr fish 200 times.

Table 1: Computed statistical descriptors of the volume of five fish of different weights. Each fish was measured 200 times.

Fish Figure 7	Mean (mm^3)	Std. Dev. (mm^3)	Max (mm^3)	Min (mm^3)
a	2425,6	5,87	2436,6	2406,4
b	2059,7	10,67	2080,5	2031,8
c	740,76	7,02	751,5	724,37
d	590,46	2,23	601,6	589,42
e	555,34	3,47	561,1	546,65

In the Table 1, It can be observed that computed volumes have low variability. Only in the case of fish 2 the standard deviation (Std.Dev.) was superior to $10mm^3$. Another observed result is the fact that high volume variability is not related to the fish volume.

The use of the density calculated in the Equation 12 and its use in the estimation of the voxel weight (V_w) is validated. For this, we take into account the customer restrictions. Specifically, the fact that the weight deviation should not exceed the $\pm 10gr$ range, when it is selected the fixed weight strategy (i.e. cut all slices using a fixed / previously selected weight).

To test if this specification is respected, we apply the following steps:

- Scan one selected fish to determine each V_i.

Table 2: The behavior of the weight for an 803 gr fish cut in 5 peace. 150 measures by each fish.

Weight (gr)	Mean (gr)	Std. Dev. (gr)	Max (gr)	Min (gr)	Max-Weight (gr)	Weight-Min (gr)
135	138,25	0,71	139,29	136,51	4,29	-1,51
140	145,35	0,38	146.41	144,53	6,41	-4,53
135	139,31	1,12	141.18	135,47	6,18	-0,47
121	124,84	1,20	127.75	120,83	6,75	0,17
94	96,44	1,80	99.90	91,36	5,90	2,64

- Weight the fish (T_w) and calculate the density using the Equation 12.
- Using the ρ and V_i, calculate the W_i (Equation 13) that is the weight associated to the i_{th} image (see Figure 6).
- Cut the fish at random places and measure the slice length and weight using a rule and a precision scale.
- Using the length of the fish slice, estimate the weight accumulated by each slice weight of the profiles (W_i).

Results can be seen in Figure 9. It shows 5 slices obtained from a fish with 803gr of weight. We have calculated the individual weight of each slice and scanned 150 times. The Table 2 shows the minimum and maximum obtained weight measured for each individual slice. In the two last columns, it is observed that the weight of each individual slice has values that are less than the established limit ($\pm 10gr$).

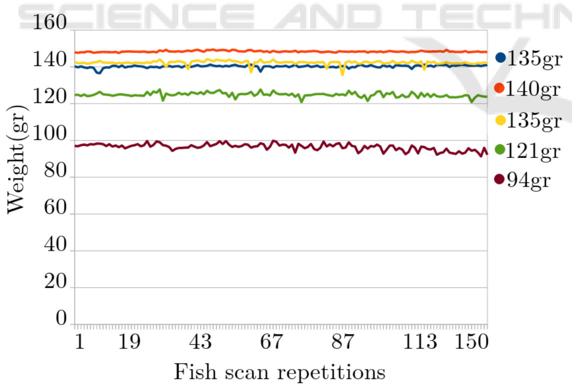


Figure 9: Estimated weight of one fish of 803gr cut in 135gr, 140gr, 135gr, 121gr and 94gr.

From the Table 2, it can be deduced that the estimated weights most of the times are greater than the real weight of the fish slice. This does not represent a problem for the proposed algorithms, because they take into account the waste produced by the cutting saw. With this, after cutting the fish, the actual weight of the obtained slices is slightly lower than the estimated weight. The volume lost at the time of cutting is always less than W_j and will depend on the thickness of the cutting saw used and the fish's area at the cutting position.

The waste produced by the cutting saw near to the tail fin is smallest than the wasted produced near to the head bone. As a positive aspect, in all cases, even without considering the waste produced by the cutting saw, always the final weights are in the desired range of $\pm 10gr$ - the customer accepted deviation in relation to the desired weight.

Taking in consideration the needs of the client, the final system prototype has been adjusted to produce more than 70 slices by minute. For this purpose, the developed system has been optimized to exploit the power of multicore CPUs by leveraging the use of a multi-thread architecture. One thread control the cameras to acquires the fish profiles and building the top and bottom images, and the rest (the free threads) are used for algorithms processing. This approach provides real-time processing, and is able to guarantee the customer's requirements concerning the number of fishes slices / minute.

The total delay of the automated vision system is the sum of the acquisition time and the processing time (see Table 3). Each fish takes between half second and a second to be processed. In huge fish, sometimes, the individual processing time of a fish is slightly bigger than one second. With this, it can be concluded that the automated vision system can perform almost in real time system.

Table 3: Behavior of acquisition and processing times for different sizes of fish in milliseconds (ms).

Weight (gr)	Acquisition Time (ms)		Processing Time (ms)	
	Max.	Min.	Max.	Min.
2260	821	717	294	170
1880	749	671	286	129
670	681	610	217	54
520	451	440	98	49
510	422	410	82	46

5 CONCLUSIONS

The main contribution of this work is the development of an automated real time computer vision system able to: 1) capturing and building a precise 3D representation of frozen fishes; and 2) accelerating the automated frozen fish cutting in the production lines at industrial level. An innovative high performance image processing method has been developed that allows to automatically infer the optimal place (coordinates) where to cut the fish portions, attaining a previously wanted / selected weight or length of the produced slices and thus reducing the waste during the cutting process. While the dataset used is still small, the experimental statistical results demonstrated that the proposed system prototype is feasible to be implemented and validated in real industry environments.

6 FUTURE WORKS

The future work aims to validate the developed computer vision system in real production lines. Also, it is planned to improve the developed system with the ability to evaluate the freshness of the produced fish portions by analyzing properties like color, shape and texture.

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