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Automated measurement of species and length of fish by computer vision

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Abstract

Trials of a computer vision machine (The CatchMeter) for identifying and measuring different species of fish are described. The fish are transported along a conveyor underneath a digital camera. Image processing algorithms: determine the orientation of the fish utilising a moment-invariant method, identify whether the fish is a flatfish or roundfish with 100% accuracy, measure the length with a standard deviation of 1.2 mm and species with up to 99.8% sorting reliability for seven species of fish. The potential application of the system onboard both research and commercial ships is described. The machine can theoretically process up to 30,000 fish/h using a single conveyor based system.

Keywords: Computer vision; Image processing; Fish; Fish species; Sorting

1. Introduction

Manual sorting of fish by species is carried out on all commercial and research fishing vessels (Strachan, 1994). The process is slow and is the main limiting factor in terms of efficiency on commercial fishing boats and requires increased labour on both types of ship. At present all fish caught by commercial fishing vessels are manually graded by species and weight in accordance with EC regulations (3703/85, 1986). There is a requirement for an automated fish sorting system capable of recording species, length and weight data. This requirement is driven by the need to reduce labour onboard vessels and to automate logging of the catch, which is required for regulatory purposes and also to enable increased traceability.

Tayama et al. (1982) describe a method for sorting species based on shape and achieved a sorting reliability of 95% for four species of fish. Wagner et al. (1987) describe a similar method and achieved a sorting accuracy of 90% for nine species of fish. Utilising colour and shape parameters to sort fish by species, sorting reliabilities of 99% for 23 species of fish have been achieved (Strachan, 1993a). However, these results were obtained on sets of only 50 of each species of fish and each fish took up to 15 s to process. In this method, for both roundfish and flatfish a grid is constructed which describes their shape as a set of 36 elements. This works well for roundfish but not for fish with large aspect ratios such as flatfish, for which it is possible that the width lines of the grid cross over. Strachan (1993a) describes a simple shape grid whereby the width lines are drawn parallel to each other to avoid this problem. However, this method requires that flatfish must be fed through the vision system with a certain orientation. This leads to increased complexity and cost in the feeding systems.

Length measurements of fish are routinely taken onboard research vessels with an accuracy of ±1 cm. This is done either using electronic measuring boards (Scantrol, Norway) or manual measuring boards where one person measures the fish and another notes the measurements, which are then later entered into a computer. Both of these methods require each individual fish to be manually handled. Computer vision systems that can automatically measure the length of fish in the

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laboratory have been described (Arnarson and Pau, 1994; Strachan, 1993b) that give errors of less than 1 cm.

The aim of this work was to develop the next generation of fish sorting equipment, employing modern hardware and programming techniques to identify species and measure length in real time. In particular this paper seeks to describe a method which determines the orientation of fish based on the calculation of the moments of a polygon, obtained from the silhouette of fish. Fish can then be fed through the vision system in any orientation on the conveyor belt, length measurements can be made with errors of less than 1 cm and species is determined based on colour and shape. This will reduce the cost of any mechanical feeding systems and increase the throughput of the CatchMeter.

2. Materials and methods

2.1. Data acquisition

Images of fish were obtained while testing in the Barents Sea onboard the Norwegian research vessel G.O. Sars during August of 2005[1] and in the Eastern North Sea and Skagerat onboard the Dana during 2001[2]. All images obtained were calibrated by the same method (Strachan et al., 1990). Images of the following fish were obtained: Long Rough Dab (*Hippoglossoides platessoides*)[1,2], Sole (*Solea vulgaris*)[2], Lemon Sole (*Microstomus kitt*)[2], Plaice (*Pleuronectes platessa*)[1], Golden Redfish (*Sebastes marinus*)[1], Deepwater Redfish (*Sebastes mentella*)[1] and Flounder (*Platichthys flesus*)[1,2].

2.2. Mechanical handling system

The CatchMeter (Scantrol, Bergen), including conveyor, light box (Fig. 1) and feeder were designed by Matcon (Kongens Lyngby, Denmark). The mechanical systems were controlled by an Omron PLC (Kyoto, Japan) interfaced to the main computer and software via an Ethernet link. Fish moved along the Volta (Karmiel, Israel) conveyor belt at 1.5 m/s and were analysed by the computer vision system.

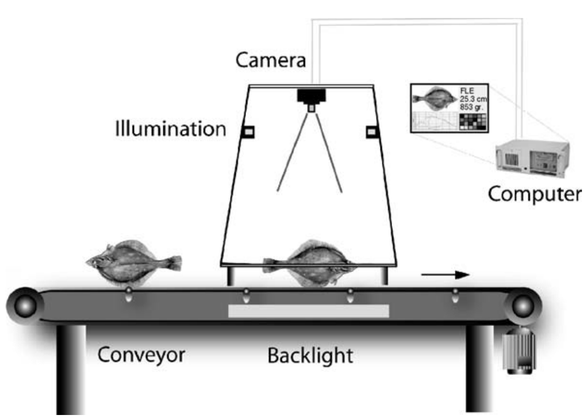

Fig. 1. Schematic diagram of the CatchMeter system.

2.3. Lighting and camera

Images of the fish, 1024 × 480 pixels with eight bits for each of the red, green and blue channels were captured by a Lumenera digital Universal Serial Bus (USB) video camera (Ottawa, Canada), with a VS Technology lens. Each pixel represented a square of side 1 mm. To avoid specular reflections from fish diffuse front lighting was supplied by 150 W GE Tungsten Halogen bulbs. In order to facilitate the fast identification of the silhouette of fish a semi transparent Volta conveyor belt was used with fluorescent bulbs underneath. Tridonic dimmable high frequency ballasts (Jennersdorf, Austria) were used to ensure the fluorescent bulbs did not flicker.

2.4. Computer and software

A desktop computer was used to run the C++ image processing software with an AMD Athlon™ 64,3500+ Processor, 1 GB of Corsair DDR400 RAM and an NVIDIA GeForce 6600 graphics card. The compiler used was Microsoft Visual C++ 6.0. A flow chart describing how the software operates is shown in Fig. 2.

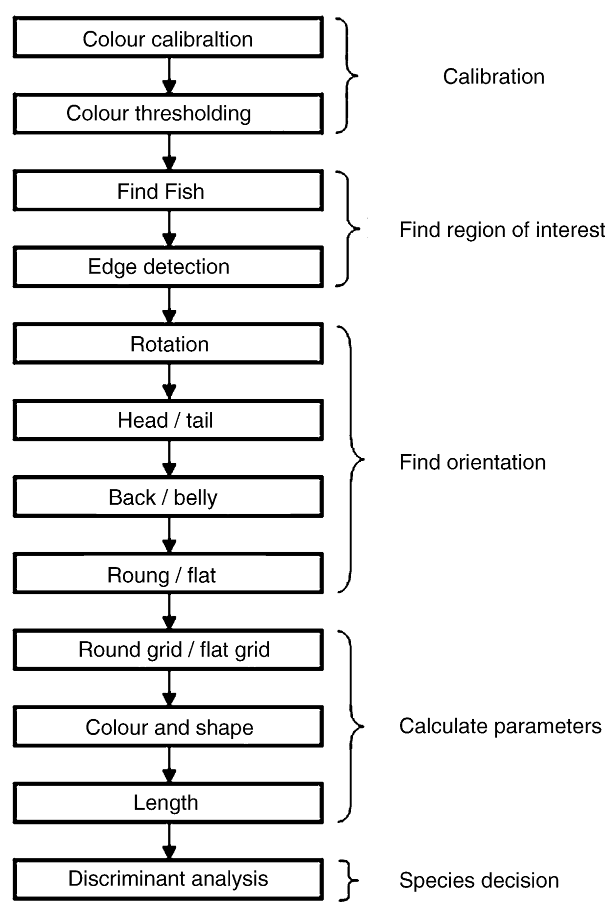

Fig. 2. Flow chart showing basic steps in the fish analysis software.

2.5. Colour calibration

Automatic colour calibrations were performed every hour to detect and correct for any variations in colour caused by the camera or lights (Strachan et al., 1990). Briefly, this involves a Macbeth colour chart (Baltimore, USA) being positioned under the camera by an actuator controlled by the PLC and then the colours being compared to reference measurements. Look-up tables were then automatically generated so that each colour could be corrected for every image taken by the camera.

2.6. Colour thresholding

Threshold colour values for the entire length of the conveyor belt were also obtained over a time of 20 s every hour. The maximum and minimum colour values of the belt defined a region in the RGB colour space. Pixels outside this region could then be further analysed to determine the presence of a fish in an image.

2.7. Finding a fish in an image

Single lines of pixels across each image perpendicular to the direction of the conveyor belt are continuously scanned for pixels outside the threshold values. If such pixels are found a small rectangular region around this point are scanned for more. Then if at least 40% of the pixels within the region (10×10 pixels) are also outside the threshold values then the process is repeated 2 cm further along (Fig. 3). If both of these rectangles contain the required number of pixels outside the threshold values, a fish is assumed to be present and a 1024×480 bitmap image is captured. This image is now scanned to make sure the whole fish is contained within the image. If it is not another 1024×480 image is captured and scanned to look for the end of the fish. The two images are then joined together so that the whole fish is contained within one image.

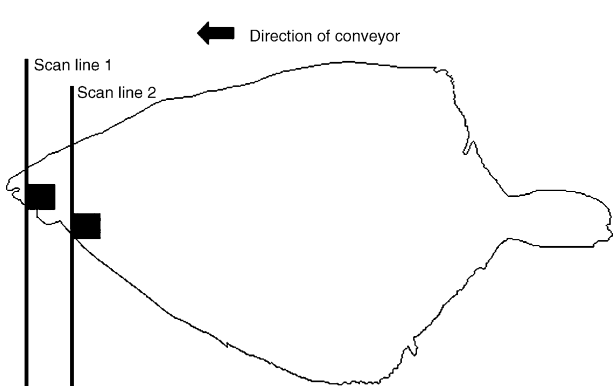

Fig. 3. Determining the presence of a fish in an image.

2.8. Edge detection

The use of backlight to increase the contrast of the silhouette of fish enabled Freeman (1974) chain code to be used.

2.9. Rotation

After the outline of the fish has been detected a rough estimation of the rotation of the fish is obtained by finding which two points are furthest from each other. If the fish is not horizontal it is rotated until it is, so that any saved images will be in a standard format. Although this does not give a very accurate measure of the orientation of the fish it is a sufficient input for the subsequent algorithms. The exact rotation is calculated after the decision has been made that the fish in question is a flatfish.

2.10. Orientation of fish head and tail

In order to define which end of the fish is the head, two widths 15% of the length of the fish in from each end are measured (Fig. 5). The larger of the two widths was taken to be the head of the fish.

2.11. Orientation of fish back and belly

For most roundfish the back is darker than the belly so a comparison between the average colour values of the top and bottom of the fish identifies the orientation. This is not the case for flatfish which tend to be coloured evenly on top and white on bottom. This similarity in colour of the two halves of the fish is used to help identify flatfish.

2.12. Roundfish or flatfish

After a fish has been split into two polygons representing the top and bottom halves, the average greyscale intensity is calculated for each area. If the difference between the average intensity of the top and bottom of the fish is greater than 15% of the total possible intensity and the width to length ratio was greater than 0.33, the fish was treated as being flat and therefore a candidate for the new flatfish algorithms. Otherwise the fish was treated as a roundfish and processed by the method described by Strachan (1993a). Redfish were found to be an exception in that the flatfish code is better suited to them due to their aspect ratio. These fish were treated separately and identified as candidates for the flatfish algorithms based on their colour and aspect ratio.

2.13. Flatfish grid

For this study a new method was developed for analysing fish of large aspect ratios (Fig. 4a) at any orientation. After the edge of a fish has been calculated (Fig. 4b) it is split up into equidistant lengths by 100 points which form the vertices of a 100-sided polygon (Fig. 4c). The moments (Appendix A)

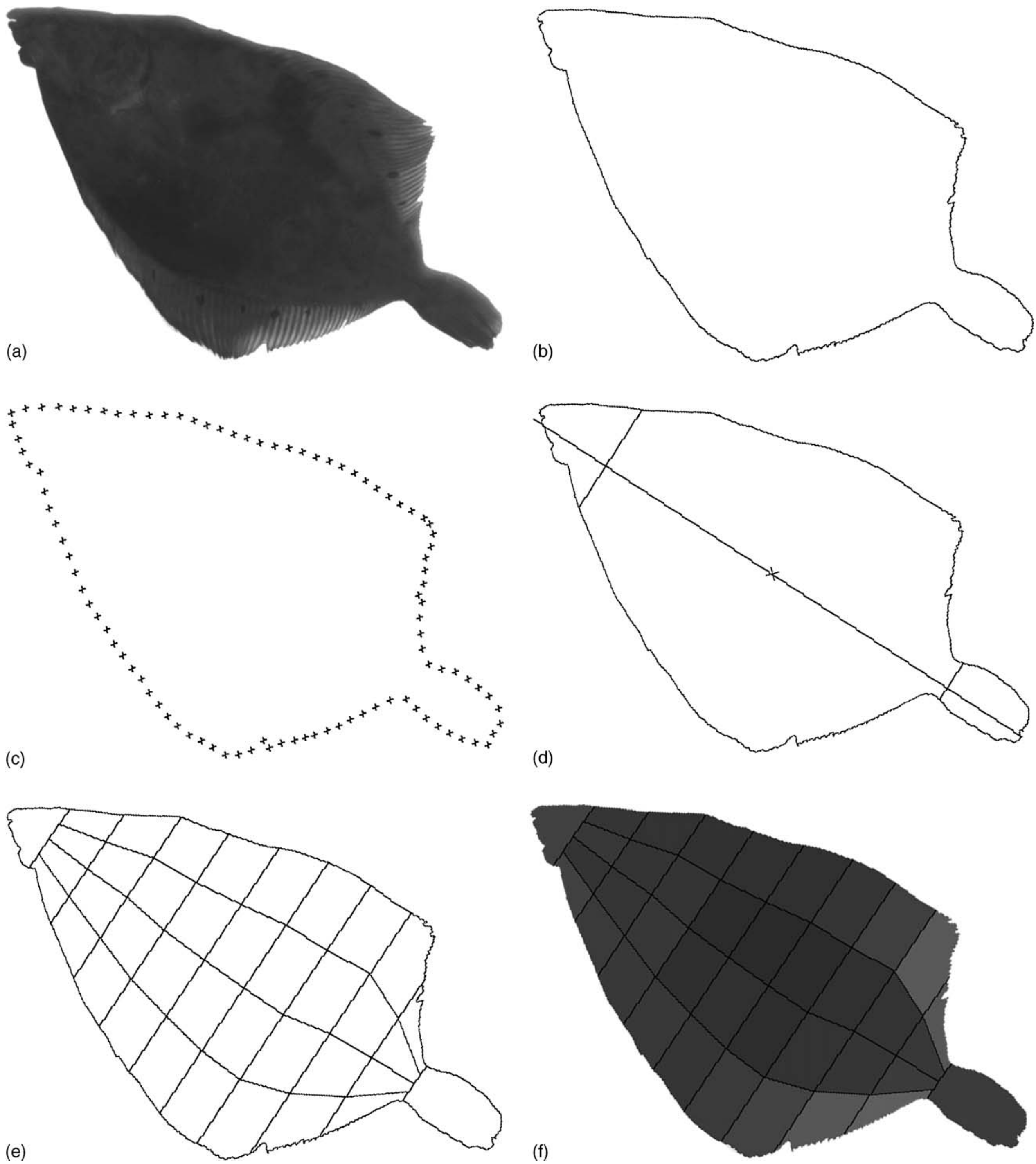

Fig. 4. (a) Original image of a plaice; (b) Outline; (c) 100 points on edge; (d) principal axis, centre of area and width lines; (e) grid; (f) fully processed.

of this polygon are then calculated using an integration technique (Strachan and Nesvadba, 1990). From this the centre of area and the principal axis are calculated. This axis gives a rough indication of the orientation of the fish, which is then used together with the chain code to find the optimal head and tail point of the fish. This new axis is used to calculate the true orientation of the fish. Perpendicular lines are drawn to the central line of the fish 15% in from each end, these widths can then be used to decide which way around the head and tail are (Fig. 4d). After the rotation and orientation of the fish has been decided 10 perpendicular widths are drawn in and three horizontal lines that split each segment into four grid elements across the width of the fish (Fig. 4e). When the grid has been drawn the average colours in each grid element (Fig. 4f) along with data regarding the shape of the fish (10 equidistant width measurements along the length) can be

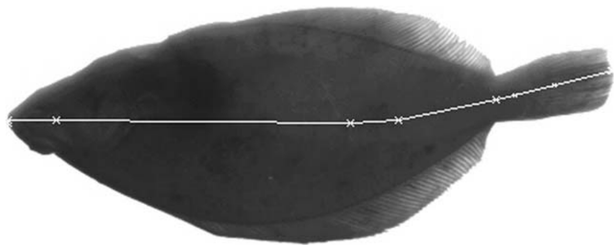

Fig. 5. Image of a processed Dab showing length measurement line.

used to make an online classification by comparing them to a set of equations that describe each trained species generated by a canonical discriminant analysis.

2.14. Colour and shape

The average red, green and blue colours in each grid element are calculated and then all of the 124 (114 colours and 10 shapes) variables are normalized to give values between 0 and 1. Shape variables are normalised by dividing them by the square root of the total area of the fish, colour variables are normalised by dividing them by 256. The colour and shape data were then processed to distinguish the species of fish by utilising canonical discriminant analysis.

2.15. Length

The CatchMeter estimates length by obtaining a line that accurately describes the length of fish in any orientation or deformation. The line was drawn between eight points along the central axis of the fish as shown in Fig. 5. One point on the tip of the nose or one between the upper and lower jaw if the mouth is gaping and one 10% along from this point. One point at approximately 60% and another at 70% from the head of the fish, this is to avoid any belly flaps and fins. Then another four points in the tail of the fish, the first three are in the middle axis of the tail and the final point is found by scanning perpendicularly away from the last point on the central axis until enough data is acquired to choose an optimal point on the end of the tail. The tail and mouth require more computation in finding the optimal points to describe the overall length as both can be deformed in many orientations especially for roundfish. The length of both round and flatfish is obtained by the same method although in practice flatfish require less computation as they tend to be more symmetrical and deform less in shape.

2.16. Canonical discriminant analysis

Canonical discriminant analysis is a dimension reducing method derived from principal component analysis and canonical correlation. Given a number of classification variables (species), with a number of samples (fish) per species and with a certain set of variables describing each fish, canonical discriminant analysis finds the linear combination of the variables that maximizes the ratio of between-group and within-group variation. The canonical variates can then be evaluated and scores obtained so that unclassified observations can be assigned to a group whose mean score is closest. The classification score (C_i) for each species (i) can be calculated for each fish from the linear combination of the classification coefficients (C_{ij}):

$$C_i = \sum_{j=1}^{j_{\max}} C_{ij} Q(j) + C_{io},$$

where $i = 1,2 \ldots n-1$ (n is the number of species of fish), C_{io} is a constant, $Q(j)$ denotes the actual values of the variables and $j_{\max}$ is 124 (114 colour variables and 10 shape variables). To obtain average classification scores for each species of fish, the system was first trained with 100 fish of each species to be tested and then unclassified fish could be assigned to a species whose average was closest. Fish whose discriminant score lay outside the 95% confidence interval for their species were classified as unknown.

3. Results

Every fish used in this test was correctly identified as a candidate for the flatfish algorithms based on their aspect ratio, top and bottom half average greyscale intensity and colour. When analysing the fish used to train the system all 100 fish for each of the seven species were correctly classified. When analysing the test sets only five deepwater redfish were incorrectly classified as golden redfish. For each of the seven species at least one and at most 12 fishes were classified as unknown, see Table 1 for a full breakdown of the results.

To test the length measurement algorithms a single Greenland Halibut was measured 100 times, in varying positions and rotations. The length measurements had a standard deviation of 1.2 mm for the 413 mm fish (Fig. 6), the reference being a meticulous manual measurement by a marine scientist with a measuring board.

Table 1
Results for the species sorting of flatfish in the Barents Sea

Species	No. of calibration fish sorted correctly	Sorting reliability (%)	No. of test fish sorted correctly	Sorting reliability (%)
L.R. Dab	100/100	100.0	399/400$^{(1)}$	99.8
Sole	100/100	100.0	394/400$^{(2)}$	98.5
Lemon sole	100/100	100.0	397/400$^{(3)}$	99.3
Plaice	100/100	100.0	399/400$^{(4)}$	99.8
Flounder	100/100	100.0	398/400$^{(5)}$	99.5
D. Redfish	100/100	100.0	383/400$^{(6)}$	95.8
G. Redfish	100/100	100.0	396/400$^{(7)}$	99.0
Total	100/100	100.0	2766/2800	98.8

Misclassified and unknown fish: (1–5, 7) classified as unknown; (6) 12 as unknown and five as Golden Redfish.

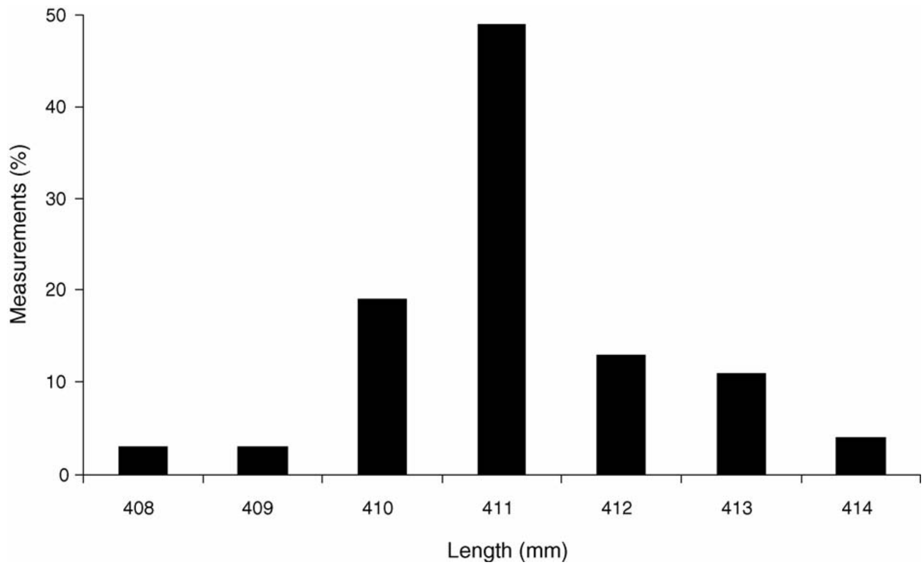

Fig. 6. Length measurement test for a single Greenland Halibut measured 100 times.

4. Discussion

The results show that it has been possible to sort seven species of fish with up to a reliability of 99.8%. Only fish with large aspect ratios were included in this study and this limited the number of species available, in practice the system can be trained with more species as required. It has been shown that the system can measure length with a standard deviation of 1.2 mm. This variation is far within the current maximum allowable error of 1 cm as dictated by EC regulations on research and commercial fishing vessels (EC, 1986).

The misclassification of five deepwater redfish was a result of the fact that they were small (5–10 cm) juvenile fish, which are not as distinctive in colour and shape as the adult fish. Increasing the size of the training set to include more juvenile fish and increasing the resolution of the images could solve this problem.

For all seven species of fish at least one and at most 12 of each test set were classified as unknown. This situation usually arises due to fish being deformed in some way. It was decided that it was more acceptable to classify a fish as unknown and sort it out, rather than risk misclassification. Further optimising the confidence levels could reduce the number of fish classified as unknown but more data would be required in order to do this.

It was found that increasing the size of the training sets did not necessarily lead to better classification scores. The important factor was to include an even distribution of varying sizes and shapes of each species of fish, 100 fishes was approximately the minimum number of fish required to represent this range in the training set. Further tests showed that increasing the number of species did not reduce the classification accuracy, but introducing different species that were similar in size and shape did.

The decision to use 114 colour and 10 shape variables in the analysis was based on findings by Strachan (1993a). In this paper it was shown that using only colour or shape data in the analysis led to a reduction in the classification accuracy. It was also shown that using fewer colour variables led to a decrease in classification accuracy.

It should be noted that the results shown in Table 1 were obtained by including images from each source in the training sets and then classifying images from all sources. Although the lighting setup and calibration method were designed to be the same in the 2001 and 2005 cruises, slight differences in the systems could lead to a reduction in sorting accuracy when treating the data from each cruise as equivalent. Decreased sorting accuracy could also occur when more species are included or fish from only one sea area or time of year are used in the training set. There is a therefore a need to use training data from different sea areas and times of year in order to encompass both seasonal and spatial variation.

The computer vision system is currently installed on the G.O. Sars, where it will be used in routine fish stock surveys. The system is of value on research vessels since it automates previously manual processes and can present new catch information that is usually unavailable such as the colour distribution of fish and it can perform length measurements more quickly and accurately than current methods. This length data can be used along with species and catch area information to get an accurate estimation of weight (Coull et al., 1989). The system is also of value on commercial fishing vessels since the manual sorting of fish by species is usually the efficiency-limiting factor in terms of getting fish into storage freezers as quickly as possible. Since the machine can potentially log an entire catch it may also be of use as a potential method for monitoring discards.

The software can fully analyse and classify each fish in 20–100 ms depending on the size using an AMD Athlon^{TM}

64,3500+ processor. The limiting factor in the throughput of the machine is how fast the fish can be fed along the conveyor. Using a smooth Volta FHW2 belt it was found the maximum belt speed that is possible was 1.5 m/s. When the belt was run at a faster speed the belt slipped under the fish, especially the larger >50 cm fish. The maximum throughput achieved on the ship was 7200 fish/h, which required two people feeding the system. A mechanical feeding system has been designed for integration with the computer vision system by Matcon and will be trialled in 2006. The introduction of this feeding system would offer a theoretical maximum throughput of 3600 1 m fish/h or 30,00010 cm fish/h.

Before the operation of the system is such that it could be fully implemented on research and commercial fishing vessel a number of issues still must be addressed. The feeding system has been designed but was not tested during this sea trial so fish were fed onto the conveyor manually. The feeding system must be built and tested. Many flatfish are coloured on top with a generally white underside. These fish were classified based on their coloured side. The feasibility of sorting them based on their underside must be investigated along with the possibility of a feeding system that could flip these fish over. It may be desirable to reduce the size of the machine which is currently 3.5 m in length, especially if it is to be introduced on smaller fishing vessels. A user interface must be designed and tested to allow non-expert people to operate the system. In order to facilitate integration with existing conveyor systems on ships the requirement for backlight must be circumvented. Research into using more robust methods of edge detection must be carried out for this. If throughput is to be increased further the feasibility of analysing multiple fish in one image must be investigated. More data must be acquired and from different sea areas to investigate what problems may arise given the fact that fish will appear different in size and shape depending on age, sex, time of year and sea area. The feasibility of detecting whether flatfish are right or left sided should be investigated along with how to treat fish that have resulted through interbreeding of different species.

5. Conclusions

A method for automatic flatfish species detection by a computer vision pattern recognition system has been described. The machine is currently installed on a Norwegian research vessel the G.O. Sars. During testing it recognised flatfish by species with up to 99.8% accuracy for seven species by the method described in this paper and measured length with a standard deviation of 1.2 mm. The system can also recognise roundfish with an accuracy of approximately 99% by a similar method (Strachan, 1994). The throughput of the machine is limited only by the feeding system which is in the design phase and will offer a capacity of 3600 1 m or 30,000 10 cm fish/h. The machine is to be used to offer detailed catch information to scientists on the research ship and the potential commercial value of the system is apparent but yet to be realised.

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Appendix A. Moments

Moments can be used in image processing and pattern recognition to calculate the principal axis and centre of area of an object described by a polygon (Bhanu and Faugeras, 1984; Bernstein, 1986). Furthermore, it is possible to evaluate the moments of a polygon based on the vertices alone (Wilf and Cunningham, 1979; Strachan and Nesvadba, 1990).

Any two dimensional shape can be represented by a density distribution function $f(x, y)$. The pq-th order moments are defined as

$$M_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q \, \mathrm{d}x \, \mathrm{d}y.$$

If $f(x, y)$ is piecewise continuous then:

$$M_{pq} = \sum_x \sum_y x^p y^q f(x, y).$$

The first moment M_{00} gives the area of the shape, the second M_{01} and third M_{03} give the 'moments of inertia' about the x and y axes, respectively. These moments can be used to find the centre of area of the shape:

$$x_c = \frac{M_{10}}{M_{00}} \quad \text{and} \quad y_c = \frac{M_{10}}{M_{00}}.$$

They can also be used to calculate the angle T of the axis of minimum inertia or principal axis of the shape:

$$T = \frac{1}{2} \arctan \frac{2(M_{00}M_{11} - M_{10}M_{01})}{(M_{00}M_{20}) - (M_{00}M_{02} - M_{01})}.$$

References

Arnarson, H., Pau, L.F., 1994. Pdl-Hm – morphological and syntactic shape classification algorithm – real-time application to fish species classification. Mach. Vision Appl. 7 (2), 59–68.

Bernstein, H.J., 1986. Determining the shape of a convex n-sided polygon by using $2n+k$ tactile probes. Inform. Process. Lett. 22, 255–260.

Bhanu, B., Faugeras, O.D., 1984. Shape matching of two-dimensional objects. IEEE Trans. Pattern Anal. Mach. Intelligence PAMI-6 (2), 137–156.

Coull, K.A., Jermyn, A.S., Newton, A.W., Henderson, G.I., hall, W.B., 1989. Length/weight relationships for 88 species of fish encountered in the North East Atlantic. Scot. Fish. Res. Rep., 43.

EC Commission Regulation 3703/85, 1986. Common Fisheries Policy, Community Grading Rules, a Guidance Note to the Fishing Industry. U.K. Fisheries Departments.

Freeman, H., 1974. Computer processing of line-drawing images. ACM Comput. Surv. 6 (1), 57–97.

Strachan, N.J.C., 1993a. Recognition of fish species by colour and shape. Image Vision Comput. 11 (1), 2–10.

Strachan, N.J.C., 1993b. Length measurement of fish by computer vision. Comput. Electron. Agric. 8, 93–104.

Strachan, N.J.C., 1994. Sea trials of a computer vision-based fish species sorting and size grading machine. Mechatronics 4 (8), 773–783.

Strachan, N.J.C., Nesvadba, P., 1990. A method for working out the moments of a polygon using an integration technique. Pattern Recogn. Lett. 11, 351–354.

Strachan, N.J.C., Nesvadba, P., Allen, A.R., 1990. Calibration of a video camera digitizing system in the Cie L- Star U-Star Upsilon-Star colour space. Pattern Recogn. Lett. 11 (11), 771–777.

Tayama, M., Shimadate, N., Kubota, N., Nomure, Y., 1982. Application for optical sensor to fish sorting. Reito (Tokyo). Refrigeration 57, 1146–1150.

Wagner, H., Schmidt, U., Rudek, J.H., 1987. Distinction between species of sea fish. Lebesmittelindustrie 34, 20–23.

Wilf, J.M., Cunningham, R.T., 1979. Computing Region Moments from Boundary Representations. JPL Publication 79-49, Jet Propulsion Laboratory, California Institute of Technology, Pasadena, California.