Development and Evaluation of Advanced Morphological Algorithms for Automated Fish Measurement in Sustainable Fisheries

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***Abstract*—Accurate identification and measurement of fish populations present critical challenges in ecosystems characterized by significant morphological variability. This work presents morphological algorithms developed to enhance automated fish measurement processes in freshwater fisheries, with potential applications in coastal and marine ecosystems. Key contributions include developing algorithms tailored for non-linear morphologies and integrating these advancements into the "ICTIOBIOMETRIA" application, which systematically records fish biometric data such as weight, dimensions, and capture locations. The dataset used originated from three primary sources: images inherited from prior collaborators, samples collected in partnership with the Ichthyology and Fisheries Laboratory at the Federal University of Rondônia, and acquisitions from fish markets. These sources provided 588 images representing diverse fish species from the Madeira River basin in Porto Velho, Rondônia, located in the Western Amazon. A dataset from established authors was also used as a reference to validate the proposed measurement models, ensuring a comprehensive comparative analysis that reinforced the robustness of the developed methods. To address challenges posed by larger fish and those exhibiting non-linear shapes, algorithms were developed and implemented to manage these characteristics effectively. Among the three measurement methods evaluated, the skeletonization method demonstrated superior performance, reducing the relative total error by 1.56%, and demonstrating robustness across diverse morphologies.**

I. Introduction

Accurate fish monitoring is crucial for sustainable fisheries but is hindered by morphological variability among species. A 2020–2021 prototype achieved average relative errors below 10% (1), yet its reliability was compromised by error variability across species. This work enhances existing methods to improve applicability in commercial fishery contexts.

Fish lengths are typically classified as Total (TL), Furcal (FL), and Standard (SL) (2). The ICTIOBIOMETRIA system, based on (1), estimated these measurements by connecting nine key points along the fish's body. Despite improvements, the method faced limitations due to morphological diversity among species. More robust solutions may require non-linear approaches (3). Systems such as CatchMeter (4), though promising, struggle with generalization due to training on a limited number of species.

The present study addresses limitations identified in existing methodologies for automated fish measurement. Deep Convolutional Neural Networks (DCNNs) have demonstrated effectiveness in image analysis applications. However, (5) reported difficulties when applying DCNNs to fish biometric prediction, particularly regarding complex morphological variations and computational resource requirements. Similarly, (6) employed comparable techniques for shrimp measurement, though these methods exhibited limited applicability to fish species. Figure 1 presents the measurement types examined in this work (2).

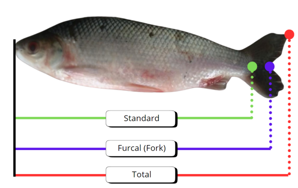


Fig. 1. Examples of the types of measurements addressed in this work.

This work builds on prior studies in Python-based data processing (7; 8; 9) and graph algorithms (10) to implement image-based fish measurement. Skeletonization and graph conversion techniques (11; 12) were applied to improve pixel-to-centimeter accuracy.

The goal is to refine detection and measurement algorithms to support fisheries and research needs by improving the generalizability and morphological adaptability of biometric extraction. This will be achieved by integrating these enhanced techniques into the Ictiobiometria application.

II. Material and Methods

The dataset comprises 588 images of fish from the Madeira River basin, collected in partnership with the Ichthyology and Fisheries Laboratory at the Federal University of Rondônia (UNIR) and local fish markets. Each image includes a reference object used for pixel-to-centimeter conversion (see Equation 1) and was captured using the Ictiobiometria app, which also records length and weight data. Manual measurements were conducted to ensure label accuracy. For comparative validation, an external dataset was also used (1). Figure 2 presents a visual overview of the methodological process developed in this work.

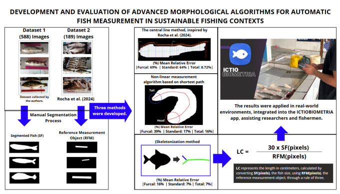


Fig. 2. Graphical representation of the methodological process adopted

A. Measurement and Evaluation

Fish lengths were calculated by converting pixel distances into centimeters using a reference object (ruler), as shown in Equation 1.

$$\text{Length (cm)} = \frac{\text{Pixel Distance}}{\text{Reference scale (pixels/cm)}} \tag{1}$$

Accuracy was evaluated using relative error, comparing algorithmic results with manual measurements and entries from the ICTIOBIOMETRIA database. A public dataset (1) was also used for external validation.

B. Dataset Preparation

Images collected via the application were manually segmented to isolate fish contours and measurement objects, resulting in two distinct masks. These segmentations form the basis for applying the proposed algorithms. Figure 3 shows the original image and its corresponding segmentation.

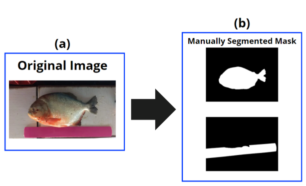


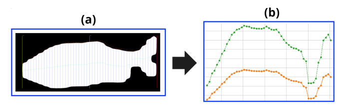
Fig. 3. Stages of dataset preparation: (a) original image; (b) manually segmented mask isolating the fish contour. The segmented reference object is visible below the fish.

C. Algorithm Based on the Center Line Method

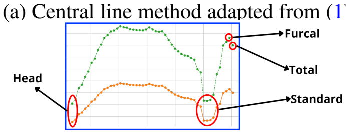
This method builds upon the center line approach proposed in (1), enhancing its precision in defining morphological features. The algorithm identifies midpoints along the segmented fish body and incrementally analyzes vertical depths at regular 5% intervals along the central axis to construct a morphological profile. These midpoints are then used to map the fish contour with higher fidelity.

Key anatomical features such as the head, tail, and measurement markers are extracted by analyzing the variation in vertical and horizontal line profiles. The method detects tapering patterns in these line heights to distinguish extremities and accurately locate the furcal, standard, and total lengths, without requiring explicit segmentation of anatomical parts.

Figure 4 presents the implementation of the center line method. In (a), a visual overlay of the measurements is shown, and in (b), the detected anatomical points (head, tail, furcal, standard, and total length positions) are illustrated.



(a) Central line method adapted from (1).



(b) Detection of furcal, standard, and total lengths, as well as head and tail positions.

Fig. 4. Visualization of the center line method and key anatomical point detection.

D. Non-linear Measurement Algorithm Based on Shortest Path

This method identifies the fish's head and tail and computes a weighted path between them using an 8-connected pixel scheme. The algorithm prioritizes centrality while minimizing distance, and uses a direction-checking mechanism to avoid loops.

To improve accuracy, weights are dynamically adjusted based on proximity to the endpoint. As the path approaches the tail, increasing penalties are applied to edge-adjacent pixels, guiding the traversal through narrow regions and ensuring stability in curved or irregular morphologies.

E. Skeletonization Method

To address non-linearity in pixel-based measurements, skeletonization was applied to extract the fish's central structure from binary segmented images. Using OpenCV, a local skeleton is generated and pruned to remove segmentation artifacts. The resulting graph highlights the two longest paths from head to tail, preserving morphological features essential for measurement, as shown in Figure 5.

Skeletonization may produce unwanted branches caused by fins or segmentation artifacts, which compromise measurement

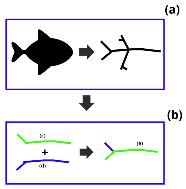


Fig. 5. Skeletonization workflow: (a) initial skeleton, (b) pruning, (c-d) longest paths, (e) final pruned skeleton.

accuracy. To address this, the skeleton is transformed into a graph structure and pruned by removing branches located before 85% of the fish's body length. A Depth-First Search (DFS) algorithm is then applied to identify and combine the two longest paths, resulting in a more accurate representation of the fish's morphology (11).

III. Results

This section presents the outcomes obtained using two datasets. Dataset 1 comprises 588 images of diverse species from the Madeira River basin, collected for this study. Dataset 2 consists of 189 images from a reference dataset (1), representing species from the Amazon River basin. All images from both datasets were manually pre-segmented to ensure precision, including both the fish and the reference object (ruler), allowing direct application of the biometric measurement algorithms, For more information, see Sections II-A and II-B.

A. Results of the Center Line Method

The Center Line Method produced acceptable total length estimates on Dataset 1, with deviations below 10%. However, furcal and standard measurements showed significantly higher errors, as reported in Table II (Section III-D). These inaccuracies are mainly due to the method's inability to accommodate morphological curvature, with deviations reaching up to 44% in curved specimens, limiting its applicability in real-world conditions.

B. Problems Found in the Shortest Path Algorithm

Despite handling curved fish well, the Shortest Path Algorithm presented critical issues, including path overestimation due to segmentation errors and infinite loops in specific cases. These problems led to inaccurate pixel counts, compromising the conversion to centimeters. As shown in Table I, significant discrepancies were observed. Moreover, it failed to maintain relative errors below 10%, as detailed in Table II (Section III-D), and was thus discarded. Alternatives such as Reinforcement Learning (RL) and Graph Neural Networks (GNNs) were considered but not pursued, as the Skeletonization Method (Section II-E) yielded better initial results.

TABLE I
Comparison of expected and detected pixel counts in Shortest Path Algorithm (Dataset 1)

Image	Expected Pixel Count	Detected Pixel Count
Image 6	3321	4584
Image 4	3741	3921
Image 1	2431	3671
Image 2	2123	1873
Image 9	3221	2674
Image 10	1546	203

C. Results of the Skeletonization Method

The Skeletonization Method was evaluated using Dataset 1, with results summarized in Table II (Section III-D). It achieved relative errors below 7.5%, showing strong performance across standard, furcal, and total lengths, and proved robust for both linear and non-linear morphologies.

However, its effectiveness depends heavily on accurate segmentation. Errors in the segmented mask, especially in species with rounded bodies, can distort the skeleton and affect measurements. A potential improvement would be the use of Convolutional Neural Network (CNN)-based segmentation models tailored to fish morphology.

D. Comparison of Measurements

The three methods developed—Center Line (Section II-C), Shortest Path (Section II-D), and Skeletonization (Section II-E)—were evaluated using Dataset 1. Table II summarizes their relative errors.

TABLE II
Relative error comparison between methods (Dataset 1)

Method	**Standard (%)**	**Furcal (%)**	**Total (%)**
Skeletonization	**7.04**	**15.68**	**7.20**
Shortest Path	17.32	39.21	15.93
Center Line	64.88	69.06	8.72

Skeletonization showed the most consistent and accurate results, handling both linear and non-linear morphologies effectively. The Center Line method was only viable for linear specimens, while the Shortest Path algorithm had variable performance and practical limitations.

1) Validation with External Data (Dataset 2): Dataset 2, comprising 189 fish, was used to validate the robustness of the proposed method. Traditional linear approaches, such as that of (1), exhibited higher error rates in curved specimens, especially large fish. Table III compares total length errors by species, showing improved accuracy with the Skeletonization Method.

The Skeletonization Method reduced mean total error by 1.56% compared to Rocha et al.'s approach, with notable gains in species with curved bodies. However, some species like "Cara" showed increased error rates due to segmentation sensitivity in complex morphologies. Improvements in standard and furcal errors were modest but consistent, confirming the method's overall robustness across diverse morphologies.

2) Comparison with Related Works (Dataset 1): The skeletonization method was compared to the previous approach proposed in (1) using Dataset 1. As shown in Table IV, the

TABLE III
COMPARISON OF TOTAL MEAN ERROR BY SPECIES: ROCHA ET AL. (2024) (1) VS. SKELETONIZATION (DATASET 2)

Species	Rocha et al. (%)	Skeletonization (%)	N
Babao	6.54	5.59	7
Bodo	10.43	8.92	4
Caparari	2.40	2.05	3
Cara	11.04	33.20	7
Coroata	2.10	1.80	1
Curimba	6.20	5.30	12
Dourada	13.08	11.19	16
Filhote	7.02	6.01	8
Jaraqui	2.59	2.22	17
Jau	10.49	8.97	10
Pacu	5.94	5.08	37
Piau	2.90	2.48	5
Piranha	9.27	7.93	3
Pirarara	13.13	11.23	15
Surubim	7.06	6.04	4
Tambaqui	57.15	25.13	6
Traira	5.84	5.00	6
Tucunare	7.43	6.36	23
Zebra	9.51	8.14	1
Mean Total Error	**10.00**	**8.44**	**189**

proposed method outperformed the prior technique across all metrics, reducing the mean total error by 3.37%.

TABLE IV
RELATIVE ERROR COMPARISON: ROCHA ET AL. (1) VS. SKELETONIZATION (DATASET 1)

Metric	Rocha et al. (%) (1)	Skeletonization (%)
Standard Error	15.54	7.04
Furcal Error	29.18	15.68
Total Error	10.57	7.20

Compared to (5), whose ensemble model achieved a 7.6% error using multiple images from different angles, the Skeletonization Method reached a comparable accuracy of 7.20% with a single image. Additionally, it uniquely enables the extraction of standard and furcal lengths, highlighting its efficiency and practical advantages.

IV. CONCLUSION

This work automated fish biometric measurements using the Skeletonization Method, achieving a 1.56% reduction in mean relative error compared to linear techniques. Integrated into the ICTIOBIOMETRIA app, the method enabled efficient and standardized extraction of standard, furcal, and total lengths.

Despite good results, accuracy remains sensitive to segmentation quality, especially in rounded species. Future improvements may include CNN-based landmark detection and contour extraction techniques to enhance robustness.

Overall, the system advances fishery data collection, reduces human error, and supports sustainable fisheries management through reliable and automated measurement.

ACKNOWLEDGMENT

C.R.C.D. acknowledges the Brazilian National Research Council (CNPq) for financial support through the productivity grant (No. 304501/2023-9). The authors also thank the Aliança Águas Amazônicas and the NGO Ecoporé for their support and collaboration during this research.

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