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Classification of guppies' (*Poecilia reticulata*) gender by computer vision

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Abstract

Labor costs of guppy growers and breeders are largely those of manual sorting (by strain, quality and gender) and counting fish. In most farms, female and male fish are grown together and sold either separately or together. Sorting fish according to gender is important for marketing as well as for breeding programs, so that a device for sorting and counting fish can potentially reduce production costs and improve quality.

A project aiming to develop sorting and counting technologies for ornamental fish growers included development and testing of image-processing algorithms for sorting guppy fish (*Poecilia reticulata)* by gender. The algorithms are derived from shape and color differences between female and male guppies. An algorithm for the determination of landmarks on fish contours was developed and found to be accurate in accordance with human judgment, enabling extraction of specific shape and color features of the tail and the body.

The algorithms were applied to three sets of images of guppies of the ‘‘Red-Blond’’ strain. Gender identification accuracy was approximately 90% using shape features, approximately 96% using color features and was slightly improved when both color and shape features were used.

Some of the components used are essential for future development of a computer vision based system for sorting and grading ornamental fish by strain and quality.

Keywords: Ornamental fish; Guppies; *Poecilia reticulata*; Gender; Sorting; Computer vision; Image-processing

1. Introduction

The annual value of the world's wholesale trade in ornamental fish (including commodities) was estimated in 2001 at 1 billion dollars (Olivier, 2001). The Free-On-Board export value of freshwater and saltwater fish in 2005 was estimated at 264 million US dollars, an increase of 50% with respect to 2001 (FAO, 2007). Ornamental fish farming is a relatively new branch of the agricultural industry in Israel. In some regions where the climate is consistently warm, tropical ornamental fish are a non-seasonal 'crop', and production and marketing can be managed like any other non-agricultural industry.

Many guppy (*Poecilia reticulata*) breeders and fans belong to local and international clubs and associations that frequently hold exhibitions and competitions. In order to create a basis for judging show entries it was necessary to establish a set of standards, used exclusively for making award decisions. In exhibitions such as those held by the International Fancy Guppy

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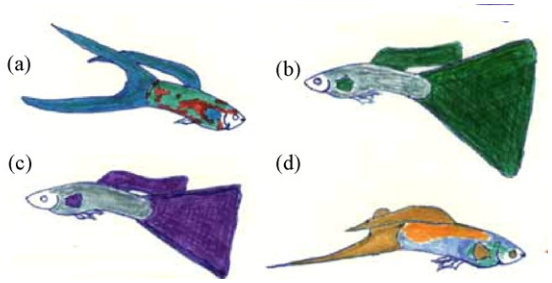

Fig. 1. Typical caudal fin shapes of male guppy (Courtesy of International Fancy Guppy Association). (a) ''Double Swordtail''; (b) ''Delta Tail''; (c) ''Veil Tail''; (d) ''Bottom Swordtail''.

Association (I.F.G.A) there are various class entries according to color, color patterns and typical shape. The quality of guppies, both in shows and in commercial trade is determined by shape and color features and is different for female and male fish. Fig. 1 shows typical caudal fin (tail) shapes of male guppies. The sword-tail should be even in taper with smooth edges. The double sword-tail should also be even in taper and equal in length. The veil should be an isosceles triangle of 45° and the delta angle should be 60°. In these three classes, the ratio of male tail and body lengths should be 1:1. For females it is usually 2:1 (Fig. 2).

Color standards are rather more difficult to define for non-scientific purposes such as exhibition judgment, so that show classes are commonly defined simply by general color (e.g. ''red'', ''blue'', ''yellow'', etc.) or color pattern (e.g. ''bicolor'', ''snakeskin'', ''multi-'', etc.).

Guppy growers and breeders base quality assessment of their fish on three types of criteria: physiology, shape and color. Physiological judgment is based on the motion of the fish (which may indicate health problems), body size (especially thickness) and straightness of spine, existence of wounds, skin scratches and other symptoms which may also indicate health problems. Shape-related features include mainly wholeness of fins, their size and shape, body/tail ratio and body proportions. Color features are complex and vary from strain to strain. In general, however, color intensity and patterns define the quality of fish. In practice, sorting and grading of ornamental fish is done according to customer's demand and with some rules of thumb.

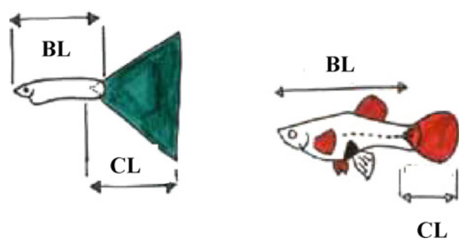

Fig. 2. Required proportions of male (left) caudal fin length to body length [1:1], and female (right) [usually 2:1] (Courtesy of International Fancy Guppy Association). BL = Body Length; CL = Caudal Length.

Since color-patch heredity of ornamental fish is a complex issue, breeding and production of high quality fish is based on selection, by repeated sorting of many fish according to gender and quality (Wohlfarth and Rothbard, 1991; Gomelsky et al., 1995). In spite of basic differences in growing methods and systems, ornamental fish growers face a common problem—the repeated grading and sorting of fish according to size, quality and gender, at various growth stages and before marketing. Manual sorting and counting operations can account for 40%–70% of total labor costs (personal communication with leading tropical fish growers in Israel) and are, inevitably, subjective and inaccurate. Due to the constant decrease in availability of farm workers and increases in labor costs in Israel, the growers' common vital objective is to reduce labor to a viable minimum. This objective can be achieved by completely or partially automating the daily tasks of sorting, grading and counting.

This paper presents image-processing algorithms developed for automatic identification of guppy gender, using the ''Red-Blond'' strain as a model. The aim of the work is to develop methods and systems based on computer vision, for sorting and grading guppies according to gender, color, size and shape (Karplus et al., 2003, 2005).

There are many image-processing methods for fish recognition and classification. Methods of processing images of edible dead fish (Tayama et al., 1982; Wagner et al., 1987; Strachan, 1993; Arnarson and Pau, 1994; Strachan, 1994; Strachan and Kell, 1995) and live fish (Castignolles et al., 1994; Savage et al., 1994; Cadrin and Friedland, 1999; Cadieux et al., 2000; Cadrin, 2000; Tillett et al., 2000; Lines et al., 2001; Tidd and Wilder, 2001; Martinez de Dios et al., 2003; Tillett and Lines, 2004) have been reviewed by Zion et al. (1999, 2000, 2007).

Wallat et al., 2002 used a machine vision system to quantify development of goldfish (*Carassius auratus*) skin color in response to different feeds. They compared pixels color to 64 color standards, generated color histograms and used them as an objective measurement of the skin color.

White et al., 2006 used 10 shape features (grid lines length) and 114 color features (average RGB values of 38 grid elements) to sort fish by species while conveyed on a belt. Their system was 99.8% accurate in classifying 7 species and measured fish length with a standard deviation of 1.2 mm. It required hourly color calibration and background measurement.

Zion et al., 2007 have recently developed a real-time underwater computer vision system and tested it on fish swimming through a narrow, transparent, unidirectional channel in a pool. Overall species recognition accuracy was 98%. An algorithm was developed for locating landmark positions on fish contours and extraction of shape-related features to classify them. Shape descriptors are less sensitive to lighting variations and are therefore preferable, in many cases, to color features. In the present work we used both shape and color features to identify the guppies' gender.

2. Materials and methods

2.1. Fish and imaging

Three groups of guppies of "Red-Blond" strain were obtained from three growers. The fish were approximately 25–30 mm long and were kept in a glass aquarium at room temperature. One day before images were taken, pairs – one female and one male – were moved into smaller aquaria (10 cm × 10 cm × 10 cm) into each of which an air stone was inserted for oxygen supply. The aquaria were numbered for identification. On the day of the imaging session, a guppy grower was invited to diagnose and characterize each of the fish to be imaged. Diagnosis included shape and color features, and gender. The fish were placed, one at a time, in a small glass aquarium (length—approx. 100 mm; depth—100 mm; width—15 mm; glass thickness—3 mm) for imaging. Fish images were acquired with a computer vision system consisting of a lighting chamber, a video camera (JVC ky-F30B 3CCD) and a frame grabber (Data Cell Limited S2200 for the first two sets, and Imaging Technology PC-RGB for the third set). Lighting for the first two sets consisted of two pairs of standard 1200 mm 40 W fluorescent lamps (Tungsram, Daylight 2300l m), covered with plastic light diffusers and mounted above and below the aquarium. For the third set, two pairs of 18 W PL lights (Osram Dulux D/E, cool white) were used for compactness. The lighting system was connected through a high-frequency electronic dimmer to minimize 50 Hz flickering. The camera focused on the aquarium from the side and on the other side of the aquarium a black velvet cloth was used for background.

The relatively small width of the aquarium (15 mm) restricted variability of the fishes' distance from the image plane of the video camera, thereby minimizing scaling and focusing problems. The fish could swim freely in the aquarium and were viewed on the video monitor. Each fish was imaged twice when it appeared in the camera's field of view and 226, 238 and 156 images respectively were acquired in three imaging sessions. Image spatial resolution was approximately 0.1 mm/pixel for the two setups. Fig. 3 presents typical images of a male and a female Red-Blond guppy as acquired by the system.

2.2. Segmentation

Since the fish images were acquired against a dark background, they were easily segmented by means of a histogram-based selected threshold. Cumulative histograms and their derivative were calculated for the RGB bands. A search was conducted for the grey level (within a known range below the characteristic levels of fish segments and above the background) at which the derivative of the histogram decreases below a certain value. This grey level was set as the threshold level for

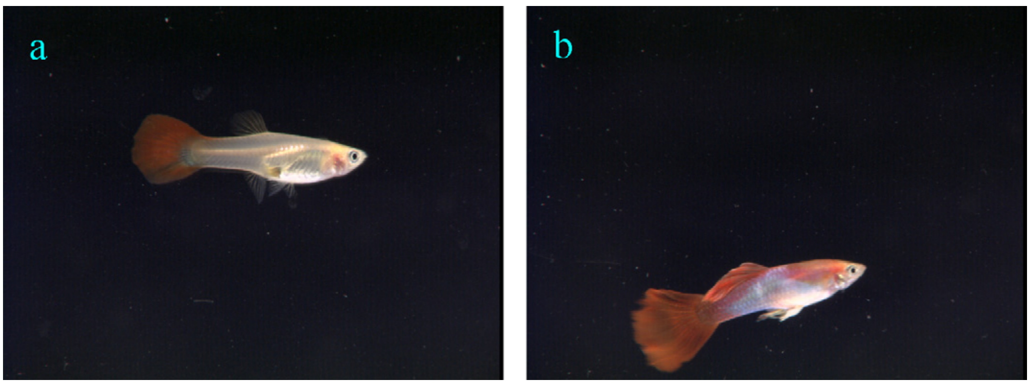

Fig. 3. Images of a female (a) and a male (b) "Red-Blond" guppy.

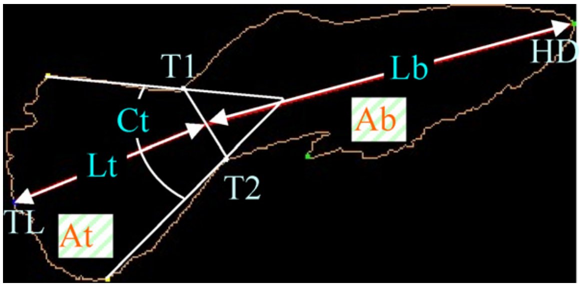

Fig. 4. Segmented image of the male guppy shown in Fig. 3b; contour landmarks (T1, T2, HD and TL) found by the algorithm; line connecting body–tail transition points (T1 and T2) which defines the geometrical border between the two. Shape features extracted include the body length and area (Lb, Ab), tail length and area (Lt, At) and the tail opening angle (Ct).

that band. A logical AND operator combined the results of the three bands for differentiating between background and object pixels. A labeling algorithm was applied to the image and the largest segment was chosen as the fish segment (Fig. 4). All other segments were eliminated as noise.

2.3. Features extraction

Since male and female guppies have some differences in shape and color characteristics, an algorithm reported by Zion et al., 2007 for landmark positioning on the fish contour was applied, specifically to search for two points (T1 and T2) which best define the transition between fish body and tail, as well as the head (HD) and tail (TL) ends (Fig. 4). Once these points were defined, shape and color features associated with the fish body and tail were extracted (Table 1 and Fig. 4). In order to assess the accuracy of the contour-landmark positioning algorithm, a comparison between the algorithm results and human decisions was made. Three persons were presented with guppy images and asked to mark head, tail and two body-tail transition points. The points were registered and their location statistics were compared with the algorithm results.

In most guppy strains, color and relative dimensions of the dorsal fin and tail are the typical visual differences between adult males and females. Males usually have large colorful fins and/or colorful bodies, while female coloring is more subdued. Since fish color must be considered and analyzed for quality attributes (one of our future objectives), using color features together with shape features for gender determination involves no extra computational cost.

The original RGB color space of the segmented image was transformed into the HSI color space. Normalized histograms of the hue values of pixels in the fish images (excluding background) were generated in order to characterize the "typical color" of the fish. Using the algorithm for landmark positioning that enables body/tail bordering, the number of pixels of that typical color (i.e. between a specific hue and saturation limits) and which belong to the whole fish, the body or the tail, can be counted. The counts were normalized by the total number of pixels (of the fish, the body or the tail, respectively) in order to account for different fish sizes, and were used as the color features for gender recognition. The features' descriptive statistics for males and females are presented in Table 1.

2.4. Classification

A Bayes classifier assuming equal a-priori probabilities for males and females alike was used for gender identification. Three tests were conducted using: 1) shape-related features (1–7 in Table 1); 2) color features

Table 1
Shape and color features used for gender classification. The descriptive statistics (in pixel units, except for the tail angle) were calculated for the three fish groups together

No.	Feature	Description	Females		Males	
			Mean	S.D.	Mean	S.D.
1	At	Area of tail	6761	3343	10,927	4848
2	Ab	Area of body	21,072	10,225	26,090	8806
3	At/Ab	Tail/body area ratio	0.322	0.046	0.411	0.073
4	Lt	Tail length	98	24	111	19
5	Lb	Body length	310	77	323	46
6	Lt/Lb	Tail/Body length ratio	0.318	0.036	0.344	0.041
7	Ct	Angle of tail opening, deg.	41	13	44	12
8	NCAw	Normalized typical color area in whole fish	0.10	0.08	0.38	0.14
9	NCAt	Normalized typical color area in fish tail	0.01	0.04	0.20	0.14
10	NCAb	Normalized typical color area in the body	0.29	0.21	0.66	0.20

Table 2
Statistical data of the differences (in pixel distances along x and y image axes) between algorithmic and average manual landmark positions (tail-body transition points—T1, T2; head—HD; and tail—TL)

	Coordinate	x T1	y T1	x T2	y T2	x HD	y HD	x TL	y TL
Males	Mean	14.3	11.6	9.0	3.9	2.8	4.4	8.5	8.6
	Median	11.2	8.1	5.6	3.1	2.5	3.4	5.5	6.2
	S.D.	13.2	11.3	10.7	4.0	2.0	3.9	9.0	8.9
Females	Mean	9.7	5.3	10.8	6.0	3.3	5.0	4.4	7.6
	Median	9.3	4.5	9.6	4.2	3.3	2.6	3.4	5.9
	S.D.	6.2	4.8	6.5	5.8	1.9	9.5	5.3	7.2

Table 3
Statistical data of maximum differences (in pixel distances along x and y image axes) between panel members' landmark positions

	Coordinate	x T1	y T1	x T2	y T2	x HD	y HD	x TL	y TL
Males	Mean	10.0	6.9	6.0	4.3	3.2	2.3	12.9	15.8
	Median	8.0	5.3	5.3	4.0	2.7	1.3	8.0	11.3
	S.D.	10.4	7.3	4.4	3.0	2.1	1.7	13.7	16.9
Females	Mean	8.5	3.0	10.5	5.6	2.8	2.1	8.0	11.6
	Median	8.0	2.7	9.3	5.3	2.7	1.3	6.7	10.7
	S.D.	4.7	1.8	5.8	3.5	2.1	1.2	4.7	6.5

(8–10 in Table 1); and 3) all features. In all cases a 10-fold cross-validation test was conducted by randomly selecting 50% of the images as a training set for the classification model, which was then tested on the other images. Average classification results of the ten repetitions are presented.

Since there were three different sets of images (of fish from different growers), the procedures were tested on each set separately, and also with one set chosen as the training set, and two others for model validation. This test was conducted in order to ascertain whether classification models require specific calibration for each fish stock. The three sets were also combined into a single set and classified as above in order to test the viability of the procedure with fish stock from different sources.

3. Results and discussion

3.1. Landmarks positioning

Tables 2 and 3 present the comparisons between manual and algorithm positioning of four contour landmarks indicated in Fig. 5, namely: head tip (HD), tail end (TL), and upper and lower body-tail transition points (T1 and T2, respectively). Images of 72 males and 51 females were analyzed. The average and median differences between the coordinates assigned to the landmarks by the algorithm and those marked by the panel members was less than 11 pixels (1 mm approximately) at all points except for T1 (the upper body-tail transition point) in the males. Guppy males have a long dorsal fin which, in many cases, extends backwards and overlaps the tail. In such cases the upper transition point, T1, is actually inside the outer image contour and not on it (Fig. 5). Hence it can only be approximated by the algorithm, which is limited to the outer image contour. Furthermore, when the transition point is hidden by the dorsal fin, it could be difficult for an observer to precisely locate it. However, the average difference between algorithmic and human positioning was less than 15 pixels (1.5 mm) even for T1, and the effect of this difference on the features extracted and on

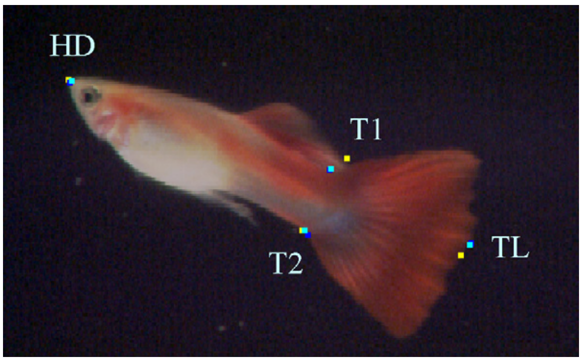

Fig. 5. Points marked on the fish image by a panel member (blue), and by the landmark-positioning algorithm (yellow).

gender classification accuracy is minuscule (see further). For head and tail points, differences were in the order of 5 pixels (0.5 mm) for males and females alike. Wilcoxon paired signed rank tests indicated that the median difference between the pairs of disagreement between the panel members (Table 3) and disagreement between their average decision and algorithm results (Table 2) is zero for x coordinate of T1, x and y coordinates of T2 and x coordinate of HD landmark and non-zero for the other 4 coordinates. In any case, the median disagreement between the panel members (Table 3) regarding all four landmarks positions was practically similar (within 5 pixels—0.5 mm) to the median difference between their average decision and algorithm results (Table 2). Since landmarks are sometimes poorly defined, there may not be objective and definitive positions for comparison with the algorithm results. Average decisions by a human panel reduce the degree of subjectivity in positions assigned to landmarks, and can therefore be used to validate these results, which clearly indicate that the algorithm performed well in defining landmarks, regardless of gender, size, and orientation.

3.2. Shape-based classification

Gender classification accuracy by shape was 90.2%, 88.2% and 90.8% respectively for the 3 sets, when the model was calibrated separately for each set. Female and male identification accuracy was 92.0% and 88.5%; 86.2% and 89.9%; and 89.6% and 92.3% respectively for the 3 sets. Of the last two sets, the best model was the one that included all 7 shape features. In the first set, the best model was the one that included only 6 features (all except Lt/Lb), but results were very similar when all 7 features were included. With all images combined into a single set, gender classification accuracy was 86.5% (89.5% for females and 83.5% for males). Of the 7 shape features used in the unified set, the highest single-feature correlation was that of the tail/body area ratio ($r = 0.588$) and the two least influential features were body length ($r = 0.106$) and the tail opening angle ($r = 0.113$). Misclassification was mainly due to the fact that the sets included lower quality fish (e.g. deformed bodies, split tails, single-sword tails and exceptionally small tails) in which some of the geometrical features were atypical. This was intentional, because a future objective is to identify irregularities, so that such samples were required for our database. If quality sorting were to precede gender classification, this would result in significantly fewer shape irregularities and better gender-classification accuracy. When the model was calibrated with one set of images and tested on the others, classification accuracies were 83.5%, 84.3%, and 80.4%. This indicates that general shape differences between guppy females and males (of the Red-Blond strain) are typical regardless of source. Calibrating the models for a specific set improves classification accuracy by up to 10%. Using only shape features has the advantage of not requiring color calibration for specific lighting conditions and imaging setups. However, to improve gender classification significantly, color features must be included in the models.

3.3. Color-based classification

The similarity between hue histograms of females and of males is clear (Fig. 6), and all of them peak – spanning the Red-Blond strain's characteristic coloration – between hue values of 330–50°. However, females' histogram peaks are lower than those of males. Furthermore, when color saturation is also considered and the typical color is defined between those hue limits and above a certain saturation value (see further), the differences become extreme.

Gender-classification accuracy by color was 95.8%, 96.3% and 96.9% respectively when the model was calibrated separately for each of the three sets. These results were achieved using a specific 'typical color' for each set, by defining a lower color saturation limit (0.30, 0.50 and 0.45 in the 0–1 range, respectively), and a single color feature, namely the typical color area of the whole fish. Female and male identification accuracies were 94.5% and 96.6%, 96.6% and 96.0%, and 96.5% and 97.4% respectively for the 3 sets. When all images were combined into a single set, gender classification accuracy was 91.8% (86.6% for females and 95.1% for males), using the 3 color features and a color saturation threshold of 0.40. When the model was calibrated with the images of one set and tested on the others classification accuracies were 78.2%, 82.7% and 86.5%, and were very unbalanced between the females and males. These results indicate that the tail and body coloration of the Red-Blond strain are very strong indicators of gender. Model calibration for each fish stock and imaging setup is required for optimal results and for a better balance in terms of class errors.

3.4. Shape and color-based classification

When shape and color features were combined, classification accuracies were 95.9%, 96.6% and 98.8% respectively, when the model was calibrated for each set. Female and male identification accuracies were

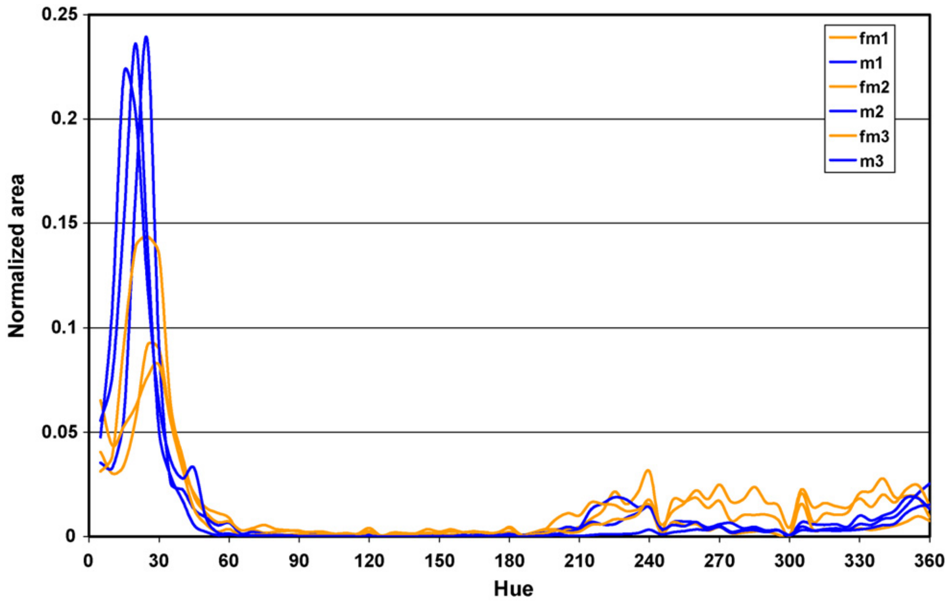

Fig. 6. Hue histograms of the complete images of 3 male and 3 female Red-Blond guppies.

93.6% and 98.1%, 97.3% and 96.0%, and 98.8% and 98.9% respectively for the 3 sets. These results are similar to those achieved using only the color features, due to the dominancy of the latter in defining gender. This may not be the case for other strains, and since the color features are based on the landmarks which define the body and tail regions (as well as the shape), the classification model would probably be more reliable for guppy strains if it included both shape and color features. This assumption will be tested and verified. With the three sets of images combined into a single set, the shape and color model classified guppy gender with 93.5% accuracy (93.2% and 93.9% respectively for females and males). Though slightly lower than the set-specific results, this is another indication that the features used are good descriptors of the observable differences between females and males of the Red-Blond strain, regardless of imaging setup and fish source.

To achieve automatic fish sorting by computer vision, it is necessary to control and manipulate fish movement in two stages: (1) to singulate and move the fish through a narrow channel that allows camera monitoring of them from the side, and (2) actual separation of fish into groups according to the sorting decisions made by the system (gender in the present case). Considerable progress has been made in our laboratory along these lines. The positive phototactic and rheotactic innate responses of guppies were used for fish guidance. Illumination, water level, flow velocity and flow direction were effective in inducing fish to move from one container to another via a narrow transparent pipe. Introduction of an obstacle into a narrow channel or narrowing a transparent pipe enhanced the singulation of guppies (Karplus et al., 2005). We were able to sort guppies at our will into two, three or four groups using multiple-arms apparatuses and switching lights (Karplus et al., 2003). The integration of fish guidance methods with computer systems is presently in progress in our laboratory.

4. Summary and conclusions

The gender of a Red-Blond strain of guppies was successfully identified by image-processing algorithms. An algorithm for contour-landmark positioning was applied to images of female and male guppies to locate head and tail tips and two points which geometrically defines where the body ends and the tail begins. It was found to be accurate with respect to average decisions made independently by three people regarding location of these landmarks.

Color and shape were found to be good descriptors of the external appearance of female and male guppies. Using shape features, a Bayes classifier classified the guppies by gender with approximately 90% accuracy. Gender classification accuracy using color features only was approximately 96%, and improved slightly when both shape and color features were used.

The classification models must be calibrated for different imaging setups and for fish from different sources (growers) to achieve optimal results. The proposed methods should be calibrated and tested with other guppy strains in order to validate reliability in classifying guppies in general.

Finally, the computer vision system should be combined with proper fish-handling mechanisms in order to achieve reliable sorting of guppies by gender.

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