UNIVERSIDAD AUTÓNOMA DEL ESTADO DE MÉXICO

FACULTAD DE INGENIERÍA

Diseño y construcción de un prototipo para medir la trucha arcoíris dentro de un flujo de agua procesando imágenes digitales

TESIS

Que para obtener el grado de Maestro en Ciencias de la Ingeniería

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Resumen

En el proceso de crianza tradicional de la trucha arcoíris, el granjero extrae individualmente los peces de los tanques de crianza y estima su longitud de manera visual, para determinar si debe cambiarlos a otro estanque acorde a su talla. Lamentablemente, esta medición visual no es exacta y genera maltrato y estrés al espécimen.

En esta tesis se presenta el diseño, construcción y evaluación de un novedoso prototipo para medir la longitud de la trucha arcoíris mientras nada contracorriente en un flujo de agua, como alternativa al método tradicional de medición por inspección visual. Este prototipo esta integrado por siete componentes: alimentador de peces, iluminación, visión, distribución, canalización; así como, caja de intermitencia y difusor de agua.

Con el desarrollo de esta investigación se presenta una alternativa para la medición de la trucha arcoíris, que en un futuro permita automatizar el proceso y mejore la exactitud de la medición manual, así como, disminuya la manipulación y estrés de los especímenes durante el proceso de crianza.

Para estimar la longitud de la trucha arcoíris se implementaron dos módulos, detección y medición, para procesar los videos adquiridos por la cámara instalada dentro del prototipo. El primer módulo detecta la presencia de un pez dentro de una imagen y en caso afirmativo activa el módulo de medición. Para la estimación de la longitud se procesa la imagen del pez para detectar los puntos (x, y) que forma la silueta del cuerpo del pez y con estos puntos interpolar una curva de ajuste para estimar su longitud.

La funcionalidad de este prototipo se ha evaluado y refinado en diferentes experimentos realizados en una granja acuícola de trucha arcoíris, ubicada en el Valle del Potrero, municipio de Ocoyoacac, Estado de México, México.

Para reportar los resultados experimentales en esta tesis, se video grabaron diez truchas arcoíris de talla adulta nadando contra corriente a través del componente de canalización del prototipo propuesto. Posteriormente, se procesaron los videos capturados en la experimentación para evaluar la exactitud en la estimación de las longitudes. En el procesamiento de la imágenes capturadas se reportan dos resultados principales, la detección y medición de los peces.

En los videos adquiridos los peces realizaron 46 nados, en los que el módulo de detección obtuvo un porcentaje de detección exitoso de 96.7 % que representa un total de 244 imágenes de peces. Por su parte, el módulo de medición obtuvo un error absoluto medio de 1.413 cm y un error relativo medio de 5.206 % sobre las longitudes estimadas en las 244 imágenes, los cuales son resultados competitivos con el estado del arte.

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Capítulo 1

Introducción

La piscicultura estudia el cultivo de organismos acuáticos tanto en aguas oceánicas como continentales, la cual implica intervención en los procesos de crianza para mejorar la producción (FAO, 2016). Esta actividad se ha incrementado drásticamente a nivel mundial tanto en producción como en consumo en las últimas décadas.

La crianza de peces necesita supervisión para ordenar los especímenes durante sus diferentes etapas de crecimiento. Dicho proceso de ordenamiento se puede realizar con base en diferentes características para separar los peces en grupos consistentes (Saberioon et al., 2016; Dowlati et al., 2012; Mathiassen et al., 2011).

Por lo tanto, los investigadores están buscando nuevos métodos o técnicas que permitan mejorar la crianza de los peces (Mathiassen et al., 2011; Dowlati et al., 2012). Para esto, es necesario monitorear, ordenar y clasificar a los peces durante las diferentes etapas de crecimiento con el fin de evitar problemas durante la crianza de peces tales como: bajo crecimiento, cantidad de alimento y medicina requerida, canibalismo y competencia desleal (Dowlati et al., 2012; Zion, 2012; Blanco, 1993).

Tradicionalmente, se utilizan métodos manuales para ordenar los peces en sus diferentes etapas de crecimiento, los cuales causan estrés y daño físico al pez. Estas técnicas convencionales de ordenamiento son laboriosas e invasivas, donde el granjero solo verifica de manera visual ciertas características del pez y lo ordena con base en estas (Romero et al., 2015; Zion, 2012; Saberioon et al., 2016).

En las últimas décadas se ha extendido el uso de visión por computadora como un método no invasivo y con resultados prometedores. Debido a esto, el procesamiento de imágenes en la piscicultura es un área de investigación activa. Particularmente, la clasificación de peces utilizando procesamiento de imágenes a través de criterios predefinidos como sexo, longitud, tamaño, masa, género, forma, piel y composiciones químicas (cantidad de sal, grasa, etc.), se observan más utilizados en el ordenamiento de peces muertos que en la planeación y mejora del proceso de crianza de especies vivas (Dowlati et al., 2012; Zion, 2012; Saberioon et al., 2016; Mathiassen et al., 2011).

En granjas pequeñas generalmente se utilizan estanques de tierra al aire libre para la crianza de peces. En estos estanques los peces tienen libertad de movimiento y están expuestos a las variaciones de iluminación ambiental. Debido a estas condiciones, los granjeros necesitan extraer a los peces para ordenarlos de acuerdo a su talla (Saberioon et al., 2016).

Por lo antes mencionado, el objetivo general y la meta de ingenirería de esta tesis son:

Objetivo general
Diseñar y construir un prototipo para medir la longitud de la trucha arcoíris de talla adulta dentro de un flujo de agua, procesando imágenes digitales capturadas en línea.

Meta de ingeniería
Diseñar y construir un prototipo basado en procesamiento de imágenes digitales cuyas características técnicas permitan medir la longitud de la trucha arcoíris de talla adulta al desplazarse dentro de un flujo de agua.

Alcances
Las granjas de crianza de trucha arcoíris identifican tres tallas principales hasta su maduración: alevín (2 a 5 cm), juvenil (5 a 12.5 cm) y adulto (12.5 a 30 cm) (Woynarovich et al., 2011). Debido al tamaño de la trucha arcoíris en su talla alevín y juvenil, por practicidad, los granjeros inspeccionan visualmente por grupos capturados en pequeños recipientes a fin de separar los especímenes mas grandes para cambiarlos de estanque. Con el muestreo solicitado para la evaluación experimental reportada en el Capítulo 3 de esta

tesis, se tiene evidencia no solo de la inspección en grupos sino también del posible traslape entre las tallas alevín y juvenil (Clasificación realizada por el granjero). Por el contrario, se observa una inspección visual uno a uno de los peces adultos, por ser ésta la verificación que determina si el pez esta listo para ser consumido.

Considerando que el granjero debe inspeccionar fuera del estanque a las truchas en un tiempo de 1 a 3 segundos para evitar que el espécimen muera, esta investigación tuvo como premisa el diseño de un prototipo para medir la longitud de la trucha arcoíris mientras se desplaza en un flujo de agua.

Por lo antes mencionado, esta investigación se centró en el análisis de la trucha arcoíris de talla adulta, para con esto determinar la viabilidad de la medición propuesta en el objetivo general de esta tesis. Igualmente, considerando que la talla adulta es la mas grande que puede alcanzar la trucha arcoíris, de resultar viable este estudio, el diseño del prototipo se podría ajustar para medir tallas alevín y juvenil. Por otro lado, el tamaño de la trucha adulta facilita su separación para ingresarlo al prototipo.

El prototipo propuesto se diseñó con base a las dimensiones físicas de la trucha arcoíris de talla adulta. Los especímenes son individualmente manipulados e insertados de forma indirecta al prototipo donde se desplazan en un flujo de agua a fin de ser analizados.

Las características analizadas de los peces pueden ser diversas tales como: tamaño, género, especie, peso y forma (Dowlati et al., 2012). En el caso tradicional de separación de la trucha arcoíris, se estima únicamente la longitud de manera visual por parte del granjero. De manera análoga al proceso tradicional de separación, en esta investigación se propone estimar la longitud del pez durante su desplazamiento como única característica para validar el prototipo.

Organización de la tesis

Con base en los artículos 57, 59 y 60 del Reglamento de los Estudios Avanzados de la Universidad Autónoma del Estado de México, esta tesis de grado se desarrolla en la modalidad por artículo especializado a ser publicado y esta integrada por los siguientes capítulos:

El Capítulo II - “Protocolo de investigación”, presenta una versión actualizada del protocolo de tesis registrado ante la Secretaría de Estudios Avanzados de esta universidad.

El Capítulo III - “Measuring rainbow trout by using simple statictics”, presenta un capítulo publicado en el libro *Emerging Trends in Image Processing, Computer Vision and Pattern Recognition* (Romero et al., 2015). En el cual se reporta una evaluación cuantitativa en la medición de la trucha arcoíris utilizando un prototipo piramidal desarrollado como trabajo previo a esta investigación.

El Capítulo IV - “A prototype to measure rainbow trout’s length using image processing”, incluye el artículo de journal enviado a revisión y posible publicación en la revista Aquacultural Engineering de Elsevier. En este artículo se describe el diseño y evaluación de un prototipo para estimar la longitud de la trucha arcoíris mientras nada en un flujo de agua.

El Capítulo V - “Conclusiones y trabajo futuro”, presenta las conclusiones obtenidas con el desarrollo de esta investigación e ilustra posibles oportunidades de trabajo futuro.

Capítulo 2

Protocolo de investigación

2.1. Introducción

Durante la crianza de la trucha arcoíris un proceso esencial es la medición de su longitud, con la cual los granjeros clasifican al pez a través de su talla que puede ser alevín, juvenil y adulto (Blanco, 1993). Tradicionalmente, en las granjas de pequeños productores de la zona central de México (e.g. Valle de Toluca, la Marqueza, Nevado de Toluca), está actividad se lleva a cabo de manera manual por los granjeros (Romero et al., 2015).

El uso de tecnología para mejorar el proceso de medición de peces, específicamente técnicas de procesamiento de imágenes se muestra como una manera factible, económica y precisa para realizar esta tarea durante la crianza de peces en granjas piscícolas (de Dios et al., 2003; Romero et al., 2015; Shafry et al., 2012; Dowlati et al., 2012; Viazzi et al., 2015).

En esta tesis se propone diseñar y construir un prototipo para medir la longitud de la trucha arcoíris dentro de un flujo de agua. En este prototipo los peces se desplazarán uno a uno por el canal, capturando imágenes digitales, con las cuales, se estima la longitud del espécimen.

El uso de tecnología en la medición de la trucha arcoíris supone una optimización al proceso de crianza que se realiza de forma manual en las granjas piscícolas de pequeños productores de la zona central de México.

2.1.1. Antecedentes y motivaciones del proyecto

Dentro del cultivo de peces, la importancia de la medición del espécimen durante la crianza para realizar una clasificación con base a su talla, radica en factores que afectan el crecimiento y la cantidad de alimento y medicamento requerido, así como propiciar el canibalismo y la competencia desleal (Blanco, 1993; Gallego et al., 2010; Dowlati et al., 2012; Hsieh et al., 2011; Ibrahim and Wang, 2009; de Dios et al., 2003; Viazzi et al., 2015).

A la fecha, la tendencia a utilizar tecnología para incrementar y mejorar el proceso de producción de peces, específicamente el análisis y procesamiento de imágenes es un área de investigación activa con resultados prometedores. (Dowlati et al., 2012; Romero et al., 2015; Hsieh et al., 2011; Ibrahim and Wang, 2009; Costa et al., 2013; White et al., 2006; de Dios et al., 2003; Viazzi et al., 2015).

Sin embargo, en las granjas de pequeños productores (e.g. en el municipio de Ocoyoacac, Estado de México), el proceso de medición de la trucha arcoíris con el cual se clasifica en tallas durante su crianza se realiza de forma manual. Este proceso consiste en la manipulación de los especímenes uno a uno para estimar su longitud de forma visual y con base a la experiencia del piscicultor se separan en grupos consistentes (Romero et al., 2015).

El interés y motivación de este proyecto consiste en desarrollar un prototipo para medir la longitud de la trucha arcoíris dentro de un flujo de agua, tomando como referencia el trabajo realizado por Romero et al. (2014). En este trabajo se desarrolló y presentó un novedoso prototipo para estimar la longitud de la trucha arcoíris utilizando procesamiento de imágenes digitales.

Finalmente, los hallazgos obtenidos a la fecha indican que la incorporación de tecnología permite mejorar el proceso de crianza de la trucha arcoíris, para medir y clasificar automáticamente al pez con base a la longitud estimada del espécimen utilizando procesamiento de imágenes digitales. Esto representa una oportunidad de mejora a los procesos empleados en granjas del municipio de Ocoyoacac, Estado de México (Romero et al., 2015).

2.2. Estado del arte

La clasificación y medición de peces ha atraído a la comunidad científica para proponer y desarrollar nuevas tecnologías que ayuden a eficientar los procesos de crianza. Es de esperarse entonces una cantidad considerable de literatura publicada. A continuación se describen investigaciones relevantes en el área.

Zion et al. (1999, 2000) creo un método para clasificar tres diferentes especies de peces, carpa común, tilapia y salmones. La técnica reportada para la clasificación se baso en momentos invariantes y algunas consideraciones geométricas como la longitud y el área del pez. Los resultados mostrados indican un 0.950, 0.997 y 0.983 de coeficiente de correlación de la longitud real con respecto a la longitud estimada de los peces, de las tres especies estudiadas respectivamente.

El trabajo mostrado por Karplus et al. (2003), se enfoco en crear y analizar tres tipos de aparatos para inducir el nado del pez lebistes a través de canales estrechos, usando la respuesta positiva a la luz y al flujo de agua de este pez. El objetivo de este estudio consistió en preparar a los peces para ser inspeccionados y ordenados por un sistema de visión por computadora. Los resultados obtenidos indican que el nado pudo ser inducido en estos peces: 96 % y 100 % de desplazamientos exitosos en machos y hembras, respectivamente.

White et al. (2006) creó un sistema basado en visión por computadora (The CatchMeter) para identificar y medir diferentes especies de peces muertos, capturados en botes pesqueros. En este sistema, el pez es transportado a lo largo de una banda en donde son capturadas imágenes a color RGB de vista superior. Este trabajo calcula la orientación y longitud de los peces utilizando momentos invariantes. Para discriminar entre las diferentes especies se utiliza análisis discriminante del color. Este sistema es capaza de identificar si el pez es de cuerpo alargado o redondo con un 100 % de precisión. Se reporta una clasificación de 99.9 % entre siete diferentes especies de peces, con una desviación estándar de 1.2 mm en las mediciones de longitud.

Utilizando visión estéreo, Costa et al. (2006) propusieron un sistema remoto para estimar la longitud de peces en jaulas marinas. Costa et al. (2006) propusieron una red neuronal para corregir los errores de medición y desarrollaron un algoritmo para filtrar las imágenes utilizando análisis elíptico de Fourier para obtener las coordenadas del contorno del cuerpo del pez. Los resultados en el error de la estimación de la longitud fueron de 5 % de la longitud real.

Zion et al. (2007) crearon un algoritmo para ordenar carpa común, tilapia y salmones. Se realizó una captura de imágenes digitales de vista lateral de cada pez mientras estos nadan a través de un canal trasparente. El algoritmo extrae el tamaño y las características invariantes del contorno de cada pez. Para realizar la separación se utilizó un clasificador bayesiano, mostrando resultados en la precisión de 98.9 %, 94.2 % and 97.7 % para las especies mencionadas respectivamente.

Dada la importancia de obtener la longitud del pez durante su crianza, Shafry et al. (2012) crearon un método llamado FileDI (Fish Length Digital Image) para obtener la longitud de los peces a partir de imágenes digitales. Este método utiliza teoría óptica y técnicas de procesamiento de imágenes para obtener la longitud de los peces. Para identificar los peces en la imagen se detectan las esquinas distintivas en el cuerpo del pez en una vista lateral, se estima la longitud del pez en pixeles (longitud de la cola a la cabeza) y con base a teoría óptica se obtiene la medida real del pez.

Adicionalmente al estado del arte presentado, existen sistemas comerciales para medir la longitud de los peces, contarlos y estimar su peso. Como es el caso del Riverwatcher Fish Counter de VAKI (VAKI, 2016), el cual mide la longitud de los peces. Este sistema es colocado en ríos en el paso de los peces, donde se capturan imágenes de vista lateral para estimar su longitud. La precisión reportada por este sistema es de 98 % y 95 % para contar y medir respectivamente.

AutoFish Sorting (Technology, 2015) es un sistema para clasificar peces basado en la longitud del pez. Este sistema desliza a los peces a través de una rampa donde se capturan imágenes de vista superior para estimar la longitud del pez utilizando procesamiento de imágenes, logrando un precisión reportada en la medición del error de 1 mm de la longitud total.

El estado del arte muestra que el análisis y procesamiento de imágenes en la estimación de la longitud del espécimen es un camino factible para optimizar el proceso de clasificación con base a su talla en las granjas acuícolas (Dowlati et al., 2012; Viazzi et al., 2015).

2.3. Planteamiento del problema

Actualmente, la medición de la longitud de la trucha arcoíris en las granjas de Valle de Toluca se realiza de forma visual, en donde, el granjero extrae uno a uno los peces, los mide visualmente y en base a su experiencia o mejor juicio los coloca en estanques de acuerdo a su talla (Romero et al., 2015). Desafortunadamente, el proceso realizado carece de exactitud (Mejia, 2013; Dowlati et al., 2012).

Como alternativa a la medición visual, existen sistemas semi-automáticos que miden al pez durante la crianza. Ejemplos de estos sistemas son Fish Counter y AutoFish System que miden al pez utilizando procesamiento de imágenes digitales (Vaky, 2014; Technology, 2015). El objetivo de estos sistemas consiste en medir al pez durante el proceso de crianza manteniendo el bienestar del espécimen durante el proceso. Para cumplir su objetivo se incorpora un flujo de agua constante para el paso de los peces.

Un trabajo previo a esta investigación en la medición y clasificación de la trucha arcoíris esta reportado en Romero et al. (2015), cuyos resultados sugieren una alternativa para resolver el problema de la medición y clasificación manual en las granjas del Valle de Toluca durante el proceso de crianza. Los resultados experimentales y el conocimiento adquirido son los elementos con los que se continua esta investigación, iniciando con la identificación de algunas limitantes que son discutidas a continuación.

Este prototipo cuenta con sistema de canalización sin flujo de agua y el ingreso de los peces al prototipo es de forma manual. Esto es, se introducen uno a uno los peces y se capturan imágenes para su posterior procesamiento. En este sistema el bienestar del pez se ve afectado por la manipulación, al ser introducidos y retirados uno a uno del prototipo. Además, la falta de oxigenación y flujo de agua en el prototipo, pone en riesgo la vida de los especímenes utilizados durante la experimentación.

De la trucha arcoíris no se espera un comportamiento cooperativo para su medición, tomando en cuenta esto, los sistemas comerciales (Vaky, 2014; Faivre, 2014) aspiran a los peces para hacerlos pasar por su sistema. Esto puede considerarse como una forma agresiva de manipulación, al ser arrastrado a través del sistema para su análisis.

Por otra parte, en Romero et al. (2015) se muestran errores en la clasificación de la trucha arcoíris en sus diferentes tallas por parte del granjero, observándose traslapes en las tallas clasificadas manualmente. Es decir, la medición y por lo tanto la clasificación manual de los peces a la fecha carece de exactitud.

2.4. Justificación

Como se mencionó anteriormente, durante el proceso de crianza de la trucha arcoíris, la medición de su longitud en granjas de pequeños productores de la zona central de México se realiza de forma manual, representando estrés y maltrato a los especímenes. Por lo tanto, esta tesis propone el diseño y evaluación de un prototipo para estimar la longitud de la trucha arcoíris dentro de un flujo de agua, utilizando procesamiento de imágenes digitales.

En un sistema para la medición de peces durante la crianza, es esencial contar con una técnica no agresiva para desplazar el espécimen. Una forma de realizar esto es proponer una técnica pasiva que promueva el desplazamiento en los canales aprovechando el nado contra corriente de la trucha arcoíris, evitando así la agresión de sistemas comerciales para medir al espécimen (Vaky, 2014; Technology, 2015). Sin embargo, este nado contra corriente solo implica la fuerza necesaria para permanecer fija y evitar con ello que la corriente arrastre al pez. Esto sugiere que el nado contra corriente de este espécimen no necesariamente conlleva un desplazamiento.

Por lo antes mencionado, se tiene la necesidad de diseñar y construir un prototipo físico que permita evaluar la medición de la longitud de la trucha arcoíris dentro de un flujo de agua, promoviendo una técnica pasiva de desplazamiento, problema que no ha sido investigado a la fecha (Dowlati et al., 2012; Romero et al., 2015; Hsieh et al., 2011; Ibrahim and Wang, 2009; de Dios et al., 2003).

2.5. Meta de ingeniería

Diseñar y construir un prototipo basado en procesamiento de imágenes digitales cuyas características técnicas permitan medir la longitud de la trucha arcoíris de talla adulta al desplazarse dentro de un flujo de agua.

2.6. Objetivos

2.6.1. Objetivo general

Diseñar y construir un prototipo para medir la longitud de la trucha arcoíris de talla adulta dentro de un flujo de agua, procesando imágenes digitales capturadas en línea.

2.6.2. Objetivos específicos

1. Proponer las características técnicas del diseño de los componentes físicos y lógicos del prototipo de medición.
2. Analizar experimentalmente la técnica de Romero et al. (2015) para adaptar su uso en la medición de la longitud de la trucha arcoíris dentro de un flujo de agua.
3. Experimentar una técnica no agresiva para promover el desplazamiento de la trucha arcoíris en un flujo de agua que no comprometa la vida del pez durante el proceso de medición.
4. Integrar los componentes físicos y lógicos del prototipo para evaluar su funcionalidad en la estimación de la longitud de la trucha arcoíris dentro de un flujo de agua.
5. Evaluar la precisión de la medición de la trucha arcoíris dentro de un flujo de agua con base a la talla estimada por el prototipo.

2.7. Metodología

Para el desarrollo de esta investigación se propone la metodología de análisis y síntesis:

- **Análisis funcional y de requerimientos**
  Colectar y analizar el estado del arte en las investigaciones relevantes de procesamiento de imágenes digitales aplicado a la estimación de la longitud de peces.

- **Análisis de factibilidad**
  Evaluar experimentalmente propuestas que promuevan el desplazamiento del pez dentro de un flujo de agua.

- **Diseño modular**

  Desarrollar un modelo físico (prototipo) que permita medir la longitud de la trucha arcoíris dentro de un flujo de agua.

  Desarrollar el software requerido de procesamiento de imágenes digitales que permita medir la longitud de la trucha arcoíris dentro de un flujo de agua.

- **Integración modular**
  Integrar el prototipo físico de la trucha arcoíris y el software de medición.

- **Experimentación**
  Evaluar experimentalmente el prototipo de medición de la trucha arcoíris en una granja piscicola.

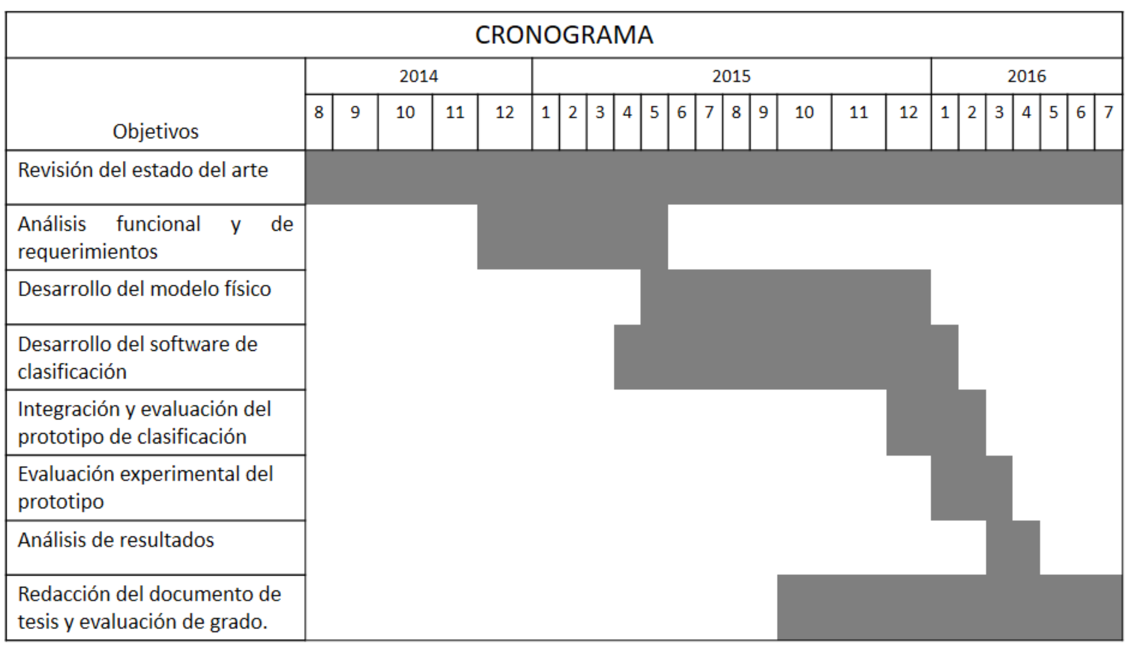
2.8. Plan de trabajo

Para el desarrollo de este proyecto de investigación se desarrolló un plan de trabajo a dos años (ver Figura 2.1), considerando las siguientes tareas principales:

- Análisis funcional y de requerimientos.

- Revisión del estado del arte en la medición de la longitud de la trucha arcoíris por procesamiento de imágenes digitales con base en características de forma.
- Desarrollo del modelo físico (prototipo).
- Desarrollo del software de medición de la trucha arcoíris.
- Integración del prototipo de medición.
- Evaluación experimental del prototipo en una granja piscícola.
- Análisis de resultados y definición de trabajo futuro.
- Redacción del documento de tesis y evaluación de grado.

Figura 2.1: Cronograma de actividades a realizar para el desarrollo del presente trabajo de investigación.



Adicionalmente al desarrollo de la investigación se cursaron y aprobaron las materias del programa en Ciencias de la Ingeniería de la siguiente manera:

Ago.-Dic., 2014 Revisión del estado del arte en la medición de la longitud de la trucha arcoíris por procesamiento de imágenes digitales, además de la acreditación de los cursos: Metodología de la investigación, con el Dr. Marco Antonio Ramos Corchado, Investigación I, con el Dr. Marcelo Romero Huertas, Algoritmos y complejidad, con el Dr. José Raymundo Marcial Romero, Estadística, con el M. en C.C Héctor Alejandro Montes Venegas y Matemáticas avanzadas, con el Dr. Juan Carlos Acosta Guadarrama.

Feb.-Jun., 2015 Análisis funcional y de requerimientos, Desarrollo del modelo físico (prototipo), desarrollo y evaluación del software de medición, además de la acreditación de los cursos: Investigación II, con el Dr. Marcelo Romero Huertas, Seminario de investigación I.

Ago.-Dic., 2015 Evaluación del modelo físico, Integración y evaluación del prototipo de medición, Evaluación experimental del prototipo en granjas acuícolas, además de la acreditación de los cursos: Investigación III, con el Dr. Marcelo Romero Huertas, Seminario de investigación II.

Ene.-Ago., 2016 Análisis de resultados y definición de trabajo futuro, Redacción del documento de tesis y evaluación de grado, además de la acreditación de los cursos: Investigación IV, con el Dr. Marcelo Romero Huertas, Seminario de investigación III.

2.9. Infraestructura requerida

Para iniciar este trabajo de investigación alguna infraestructura básica es:

- Cámaras digitales con resolución mínima de 640x480 pixeles, mínimo 30 Fps.
  Las cámaras serán utilizadas para la adquisición de las imágenes digitales.

- Materiales diversos para la construcción del prototipo (modelo físico), tales como: vidrio, lámparas, acrílico, madera, etc. usados en los componentes que integran el prototipo.
- Especímenes de trucha arcoíris viva.
  La trucha arcoíris es necesaria para la evaluación experimental del prototipo.
- Lenguaje de programación y herramientas como Matlab V.2013 con los Toolbox Image Processing, Computer Vision System y Image Acquisition.
  Se utilizará Matlab como lenguaje de desarrollo y sus toolbox para el desarrollo del software de clasificación.
- Acceso a bibliotecas digitales especializadas, tales como: Aquacultural Engineering, Fisheries Research.
  Las bibliotecas digitales marcadas muestran las tendencias e investigaciones relacionadas al trabajo.
- Equipo de cómputo con 4GB en RAM, disco duro de 1TB, mínimo 4 procesador de 3.2 GHz.
  El equipo de cómputo es necesario para el procesamiento de las imágenes digitales de la trucha arcoíris.

2.10. Contribuciones esperadas

Con el desarrollo de esta tesis se visualizan dos contribuciones originales:

- Desarrollo de un prototipo innovador que permita estimar la longitud de la trucha arcoíris dentro de un flujo de agua, procesando imágenes digitales en línea.
- Evaluación experimental del prototipo de medición in situ para cuantificar el error en la estimación de la longitud de la trucha arcoíris.

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Capítulo 3

Measuring rainbow trout by using simple statictics

A continuación se presenta un capítulo publicado en el libro *Emerging Trends in Image Processing, Computer Vision and Pattern Recognition (ISBN:978-0-12-802045-6)* de Elsevier. En este capítulo de libro se reporta una experimentación in situ estadísticamente significativa del prototipo piramidal desarrollado dentro del proyecto de investigación SIyEA 3274/2012M *Sistema inteligente para contar, medir y clasificar peces basado en visión artificial.*

Para que el sustentante de esta tesis continuara con su investigación en el área, se consideraron los resultados y oportunidades de mejora obtenidos en esta experimentación in situ.

Emerging Trends in
Computer Science & Applied Computing

Emerging Trends in Image Processing, Computer Vision, and Pattern Recognition

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Measuring rainbow trout by using simple statistics

3

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1 INTRODUCTION

Generally, small farms use a manual measuring and counting process when cultivating rainbow trout [1–4]. There are many reasons to perform such classification, but the most important are to feed the trout according to its size and to avoid cannibalism into the tanks [4]. Problems when doing a manual classification are, indistinctively, the stress and physical damage causes to the specimen when manipulated by the farmer. Moreover, we believe that this classification approach is not accurate, where the trout is taken from the water using a net and visually the farmer decide whether or not the trout should be changed to another tank.

Mexico, as well as many other countries in the world, has large hydric areas, which are ideal for aquaculture [5,6]. Taking advantage of both, its altitude and natural water resources, the State of Mexico (Mexico) has particular interest in increasing the trout's production as a sustainability and economic strategy for local small farmers [7]. Hence, this is a good opportunity to integrate technology to optimize the trout's production in this region.

That is the reason which motives our research interest in the field, where we have accomplished some results, including a research project [3] and a couple of bachelor in science dissertations [1,2]. In this paper we robustly evaluate our experimental procedure to measure rainbow trout [8] in a small farm located in the Valley of Toluca, Mexico [9], where we have observed a manual classification process as illustrated in Figure 1.

Therefore, robust experimental results are presented in this publication by using our statistical system [8] and a state-of-the-art rainbow trout image database specially collected for this article. These data corpus were collected by capturing 20 images for each of 30 specimens per size (fry, fingerling, and table-fish), counting 1800 rainbow trout images.

Some related work is observed in the literature. Hsieh et al. [10] proposed a technique to measure dead tuna fish using a colour pattern. In this work, the fish length is

Emerging Trends in Image Processing, Computer Vision and Pattern Recognition
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FIGURE 1

Manual measuring-classification process generally done in small farms in central Mexico. Note that this small farms use lined earth tanks.

estimated by proportional relationship between the fish body pixel length and an image reference scale. Ibrahim and Wang [11] measure four dead fish classes by constructing a central line along the fish body from horizontal and vertical views of the fish's body. Finally, a commercial counting and measuring system is observed in Vaki System [12]; however, there is no further information about its classification procedure.

The rest of this article is as follows. First, Section 2 describes our novel prototype designed for this research. Then, Section 3 introduces our statistical measuring approach. After that, Section 4 details our experimental framework. Next, Section 5 shows our performance evaluation. Finally, Section 6 concludes this article and draws some venues for our future work.

2 EXPERIMENTAL PROTOTYPE

In this section, we describe our experimental prototype, which has been designed as part of this research.

This novel prototype is essential to collect useful trout's 2D images; therefore, we have meticulously designed it. Figure 2 shows our experimental prototype, which has evolved from a traditional squared glass fish-cube (prototype version 1). We observed relevant issues from our first prototype and that knowledge was experimentally analyzed to obtain our second model. Note that our two prototypes have been experimentally evaluated in a trout farm; so, we have gathered special knowledge about handling the rainbow trout.

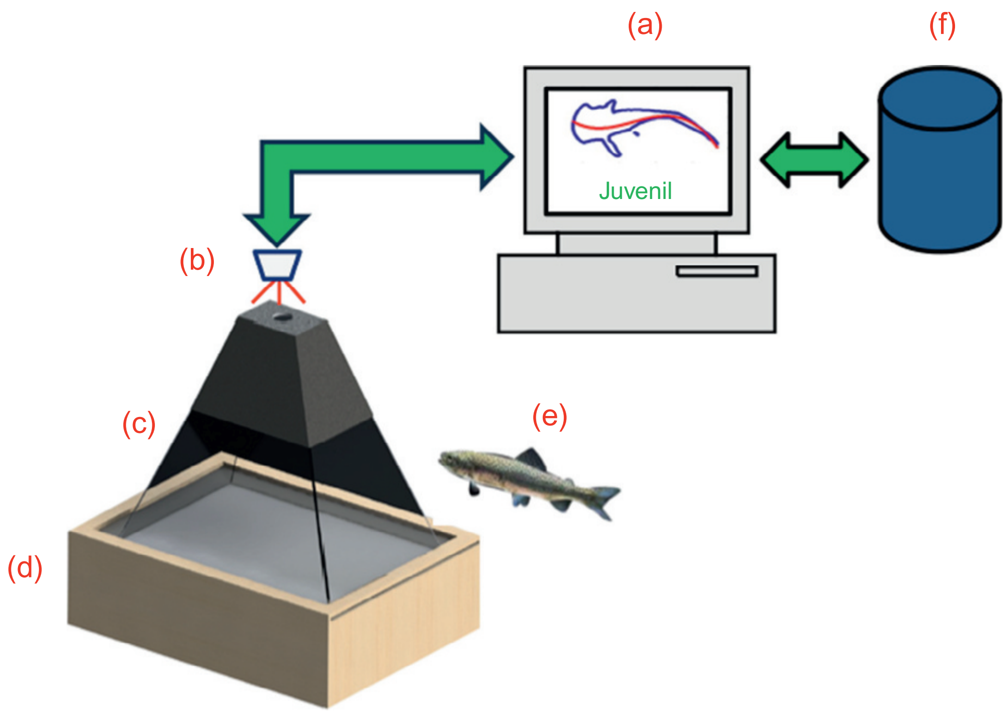

FIGURE 2

Our experimental scenario for measuring rainbow trout. (a) Statistical approach within a personal computer, (b) vision system, (c) canalization system, (d) illumination system, (e) specimen to be measured, and (f) database.

Then, as observed in Figure 2, our experimental prototype consists of three main components: canalization, illumination, and vision which are aim to collect RGB trout images using a standard personal computer.

2.1 CANALIZATION SYSTEM

We have design a novel canalization system based on opaque-glass within our prototype. This canalization system poses two main properties. The first property is regarded to its trapezoidal shape, which has been decided according to the digital camera's vision field principle. As long as such trapezoidal shape avoids reflection to be captured when taking a digital image. As its second property, we can mention that this is a two-canal tray, which prevents occlusion by taking only one fish per canal and it allows capturing two rainbow trout images per shot.

2.2 ILLUMINATION SYSTEM

To assist our vision system, we have integrated an illumination system, which distributes light in a uniform way at the bottom of the canalisation system. To do this, a light source is located to an appropriate high to distribute light uniformly over an acrylic diffuser. The light-source's high was defined by using a bisection approach and measuring the light intensity projected into the diffuser with photo resistors. We integrated this diffuse illumination to increase contrast into the image and highlighting the trout's body.

2.3 VISION SYSTEM

In order to explore economical technology for our classification system, we have used a standard 2D LifeCam Studio [13] camera in this experimentation. This camera is able to capture RGB-images with a maximum resolution of 1920×1080 pixels. In this prototype, this RGB camera is located at the top of the canalization system to capture downward-view images of the trout. Its high is proportional to the canalization base length to avoid extra data to be captured.

3 STATISTICAL MEASURING APPROACH

In this section, we present our statistical approach to measure rainbow trout.

Considering the rainbow trout natural swimming movement against the water flow and observing the trout from a downward point of view, we hypothesized that a *third- order curve* could approximate the trout's body within the water.

Different procedures can be followed to obtain a third-order curve equation. However, we prefer a simple but effective solution that could be executed online after a trout's image is captured.

Then, given n sample points (x,y) which depict the trout body, we apply minimum squares to compute a polynomial third-order equation [14]:

$$y^3 = a_0 + a_1 x + a_2 x^2 + a_3 x^3 \tag{1}$$

where a_0, a_1, a_2, a_3 are constants that gain their values by solving the $[4 \times 4]$ equation system (2):

$$\begin{aligned}
\sum_{i=1}^{n} y_i &= n a_0 + a_1 \sum_{i=1}^{n} x_i + a_2 \sum_{i=1}^{n} x_i^2 + a_3 \sum_{i=1}^{n} x_i^3 \\
\sum_{i=1}^{n} x_i y_i &= a_0 \sum_{i=1}^{n} x_i + a_1 \sum_{i=1}^{n} x_i^2 + a_2 \sum_{i=1}^{n} x_i^3 + a_3 \sum_{i=1}^{n} x_i^4 \\
\sum_{i=1}^{n} x_i^2 y_i &= a_0 \sum_{i=1}^{n} x_i^2 + a_1 \sum_{i=1}^{n} x_i^3 + a_2 \sum_{i=1}^{n} x_i^4 + a_3 \sum_{i=1}^{n} x_i^5 \\
\sum_{i=1}^{n} x_i^3 y_i &= a_0 \sum_{i=1}^{n} x_i^3 + a_1 \sum_{i=1}^{n} x_i^4 + a_2 \sum_{i=1}^{n} x_i^5 + a_3 \sum_{i=1}^{n} x_i^6
\end{aligned} \tag{2}$$

The equation system (2) can be easily solved using the matrix notation, $AX = B$, or more specifically: $X = BA^{-1}$.

After this computation, we obtained the best regression curve that adjusts the trout's body captured into an RGB image.

Then, we observe that this regression curve is related to the trout's length, which could be estimated by computing the Euclidean distance among the points within the regression curve.

Finally, given a probe-length (l_i) a classification can be done by comparing against training lengths. For this research, such comparison is performed by computing the Mahalanobis distance [15] from training fry, fingerling, and table-trout lengths:

$$d_i = \frac{l_i - \bar{x}}{s_{\bar{x}}} \tag{3}$$

Hence, a probe-trout t_i is classified through its estimated length l_i by comparing its Mahalanobis distance d_i against a predefined threshold, which in fact is the number of standard deviations that is expected to be l_i to the training mean length ($\bar{x}$).

4 EXPERIMENTAL FRAMEWORK

This section presents the experimental framework to illustrate how rainbow trout is measured using our statistical approach.

As show in Figure 3, after an RGB image is taken by our prototype, we are following a five-stage image processing to get the trout's contour. As explained in Section 3, we are measuring the trout's length using this contour.

To classify the trout's image within an image, we are performing four main steps. Firstly, an RGB image of the trout is taken using our prototype (Section 2). Secondly,

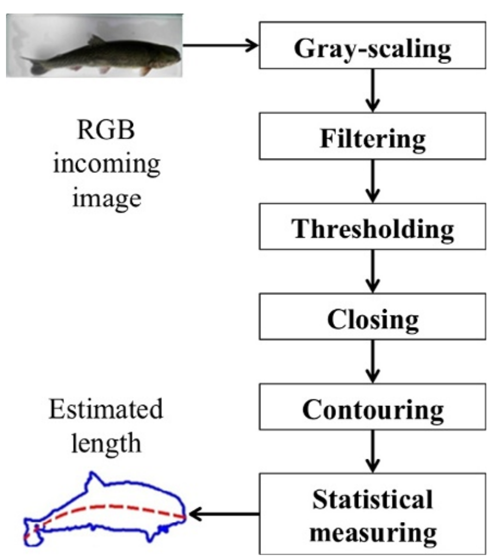

FIGURE 3

Processing an incoming RGB image to estimate the trout's length using our statistical approach.

this RGB image is processed to obtain the trout's contour. Thirdly, the trout's length is estimated by applying our statistical method (Section 3) to the trout's contour. Finally, using that estimated length, the trout is classified using a binary classification approach.

In Section 4.1, we provide more detail about our image processing step.

4.1 TESTING PROCEDURE

As illustrated in Figure 2, we have implemented a novel functional prototype which allows us to gather RGB images. After that, as shown in Figure 3, RGB images are processed using standard algorithms in the literature [16,17] until we obtain the trout's contour. Next, we apply our statistical approach to that contour, so we can estimate the trout's length. Finally, a binary classification approach is taken to classify the trout within the income image. We now detail our experimental procedure:

1. As mentioned before, we have collected a trout-image database using our prototype (illustrated in Figure 4) in a farm. This database was created

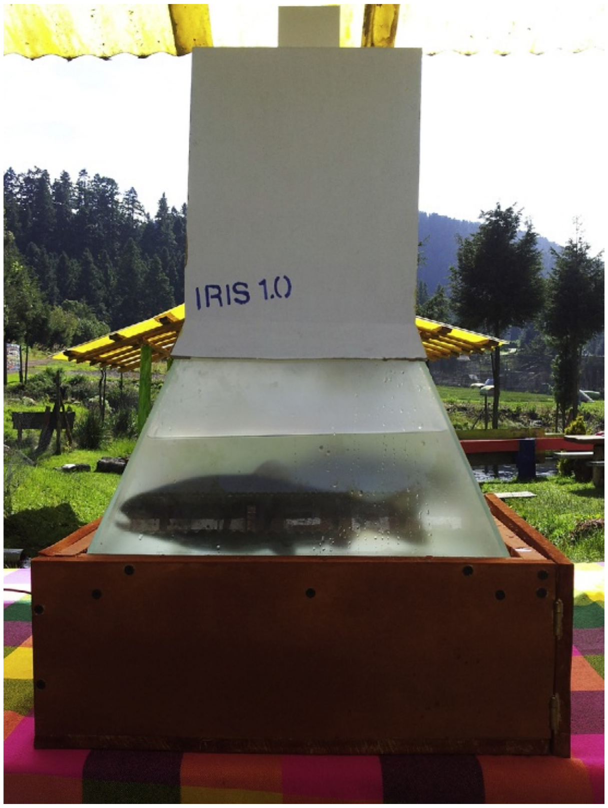

FIGURE 4

Functional prototype used within our measuring system. This prototype includes an illumination source, a pyramidal canalization compartment and a 2D camera.

Table 1 Experimental Data Images

Trout Size	Specimens	Images Per Specimen	Total Images
Fry	30	20	600
Fingerling	30	20	600
Table-fish	30	20	600
Grand total	90		1800

Table 2 Training and Testing Sets

Trout Size	Training	Testing
Fry	150	300
Fingerling	150	300
Table-fish	150	300
Total	450	900

using 30 fry, 30 fingerling, and 30 table-fish specimens, capturing 20 images per specimen. This state-of-the-art rainbow trout image database (see Table 1) was recently collected for this publication. However, for this experiment we are using only 450 images per size.

2. From our database, separate training and testing sets are defined (see Table 2). Thus, 450 images for training and 900 images for testing are used. Specifically, we have three training data sets, containing 150 images per size, namely, fry, fingerling, and table-fish trout. In every case, we selected the first five-captured images for each of the 30 specimens per size to be part of the training set. Then, we use the next 10-captured images for each of the 30 specimens for testing. By doing this, we have three testing sets (one per trout-size) containing 300 images of fry, fingerling, and table-fish, respectively.
3. From these 450 training images, training data are gathered, which in fact consist of training lengths, the arithmetic mean, and the standard deviation for each size.
4. For each testing trout image, estimated lengths are gathered as illustrated in Figures 3 and 5. To do this, we gather an RGB image using our prototype. Then, we execute a five-stage image processing: gray-scaling, filtering, thresholding, closing, and contouring. Next, we estimate the trout's length by applying our statistical approach to the contour obtained above. Finally, using this estimated length we classify the trout as fry, fingerling, or table-fish.
5. To speed up our image-processing step, our vision system gathers $[640 \times 360]$ pixels RGB-images.
6. Captured RGB values are converted into a grayscale by forming weighted sums of the R, G, and B components [16]:

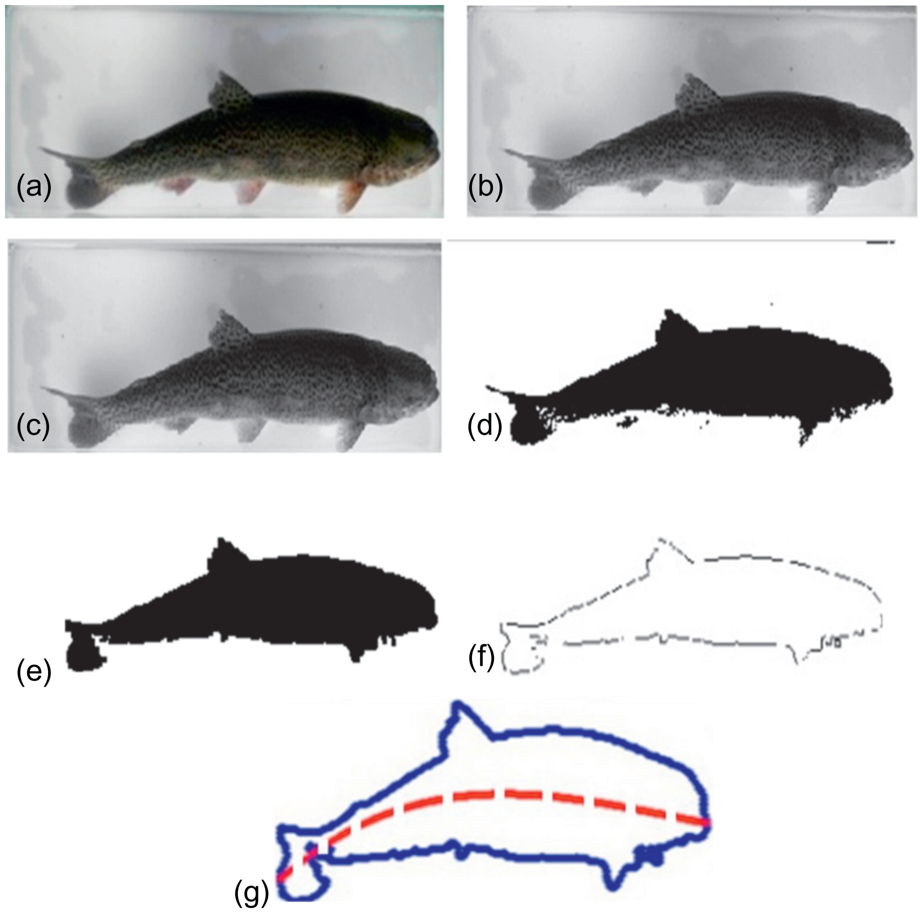

FIGURE 5

Image processing performed to measure a rainbow trout using our statistical approach. (a) RGB incoming image sensed by the vision system; (b) gray-scaling; (c) filtering; (d) thresholding; (e) closing; (f) contouring; and (g) trout's length estimated by a third order regression curve (plotted as dash line).

$$0.2989 * \mathrm{R} + 0.5870 * \mathrm{G} + 0.1140 * \mathrm{B} \tag{4}$$

7. Noise reduction is performed in every grayscale image by using a $[3 \times 3]$ Gaussian low-pass filter and $\sigma = 0.6$

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\left(x^2+y^2\right)/2\sigma^2} \tag{5}$$

8. A binary image is obtained by using a 0.245 threshold, which was calculated experimentally from training rainbow trout images.

9. The trout's body is emphasized by using a closing operation, first erosion, and then dilation with a $[5 \times 8]$ mask. This operation is the key to eliminate small clusters of pixels around the trout's body cluster.
10. The trout's contour is obtained by removing interior pixels. In this case, a pixel is set to 0 if all its four-connected neighbours are 1, thus leaving only the boundary pixels on as shown in Equation (6):

$$\text{If} \quad \begin{matrix} & 1 & \\ 1 & x & 1 \\ & 1 & \end{matrix} \quad \text{Then} \quad \begin{matrix} & 1 & \\ 1 & 0 & 1 \\ & 1 & \end{matrix} \tag{6}$$

11. Using the trout's contour, we apply our statistical measuring approach detailed in Section 3.
12. By definition, the trout's size is estimated by computing the Mahalanobis distance from this estimated length to training data (Equation 3).
13. For classification in this experiment, imagine that the complete testing-trout set (900 in total) is passed through a grid one by one in three steps. First, the grid is sized to filter only fry-trout. Then, every trout able to pass this grid is labelled as a fry-trout. Second, for the rest of the testing set, the grid is now sized to filter fingerling-trout. Every trout that is able to pass this grid is labelled as fingerling-trout. Third, for the rest of the testing set, the grid is now sized to filter table-fish trout.

    Remember that we are computing the Mahalanobis distance and this allows us to easily implement the approach above using fry, fingerling, and table-fish training data, respectively. Referring as training data the arithmetic mean and the standard deviation from each size.

    Another advantage in using Mahalanobis distance is that we can make our classification process as rigid as we decide, by defining a threshold in number of standard deviations.

    Then, in this article we are reporting classification figures from one to three standard deviations.
14. We are considering this experiment as a binary classification problem, as illustrated in Table 3. By doing this, we are collecting true positive (TP), false positive (FP), false negative (FN), and true negative (TN) frequencies [18].
15. Using values in Table 3, performance figures are generated by computing accuracy, repeatability, specificity, recall, and precision metrics when

Table 3 Binary Classification

	Actual Positive	**Actual Negative**
Predicted positive	TP	FP
Predicted negative	FN	TN

classifying as fry, fingerling, and table-fish trout. In every case, we are evaluating using as threshold from one to three standard deviations.

Accuracy, a degree of veracity, is a measurement of how well the binary classification test correctly identifies a rainbow trout's size.

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}} \tag{7}$$

Repeatability, a degree of reproducibility, is an indicator about how robustly a rainbow trout size can be identified:

$$\text{Repeatability} = \frac{\text{TP}}{\text{TP}+\text{FP}} \tag{8}$$

Specificity, a degree of speciality, rates how negative rainbow trout's size is correctly identified:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}} \tag{9}$$

Recall measures the fraction of positive examples that are correctly labelled:

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{10}$$

Precision measures that fraction of examples classified as positive that are truly positive:

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}} \tag{11}$$

5 PERFORMANCE EVALUATION

We now present performance figures when using our statistical model to measure rainbow trout in a farm.

As observed in Figure 5, our statistical approach's performance to measure a rainbow trout depends on our image processing stage. However, according to our experimental results, we believe that we have addressed main issues about capturing and processing an RGB image within our system.

As we have mentioned before, we consider this as a binary classification problem as indicated in step 13 in our experimental procedure (Section 4.1). Thus, the complete testing lengths (computed from 900 images) are compared against fry training data, using Mahalanobis distance. Then, if a testing length falls into a predefined threshold (one to three standard deviations), the respective testing trout is marked as fry-trout. Next, all remaining testing lengths are compared against fingerling training data using Mahalanobis distance as well. Again, if the testing length falls into a predefined threshold (one to three standard deviations), we label the respective testing trout as fingerling-trout. Then, every remaining testing length is compared against table-fish training data using Mahalanobis distance. Similarly, if the testing length falls into a predefined threshold (one to three standard deviations), the testing trout is labelled as table-fish-trout.

Then, as prescribed in Table 3 we count TP, FP, TN, and FN frequencies, which are summarized from Tables 4 to 6. Hence, by using these values we are able to compute accuracy, repeatability, and specificity metrics, which are presented from Tables 7 to 9 and illustrated in Figure 6.

Finally, we are computing recall and precision metrics. Tables 10 and 11 summarize these results and Figure 7 shows recall and precision results at three standard deviations.

Observing our experimental results when classifying our testing set, we score the best precision at three standard deviations: 95.93%, 93.21%, and 96.25% for fry, fingerling, and table-fish trout, respectively.

Table 4 Frequency when Classifying a Probe Set as Fry Trout at Three Standard Deviations

	1Sx	2Sx	3Sx
TP	201	259	276
FP	71	147	234
TN	529	453	366
FN	99	41	24

Table 5 Frequency when Classifying as Fingerling Trout at Three Standard Deviations

	1Sx	2Sx	3Sx
TP	149	108	39
FP	40	27	36
TN	357	309	279
FN	82	50	36

Table 6 Frequency when Classifying as Table-Fish Trout at Three Standard Deviations

	1Sx	2Sx	3Sx
TP	165	261	257
FP	7	19	10
TN	141	58	48
FN	126	21	0

Table 7 Accuracy when Classifying a Probe Set at Three Standard Deviations

Testing as	1Sx (%)	2Sx (%)	3Sx (%)
Fry	81.11	80.57	69.70
Fingerling	79.11	84.41	88.86
Table-fish	71.33	81.54	96.83

Table 8 Repeatability when Classifying a Probe Set at Three Standard Deviations

Testing as	1Sx (%)	2Sx (%)	3Sx (%)
Fry	73.90	78.84	95.93
Fingerling	63.79	80.00	93.21
Table-fish	54.12	52.00	96.25

Table 9 Specificity when Classifying a Probe Set at Three Standard Deviations

Testing as	1Sx (%)	2Sx (%)	3Sx (%)
Fry	88.17	89.92	95.27
Fingerling	75.50	91.96	75.32
Table-fish	61.00	88.57	82.76

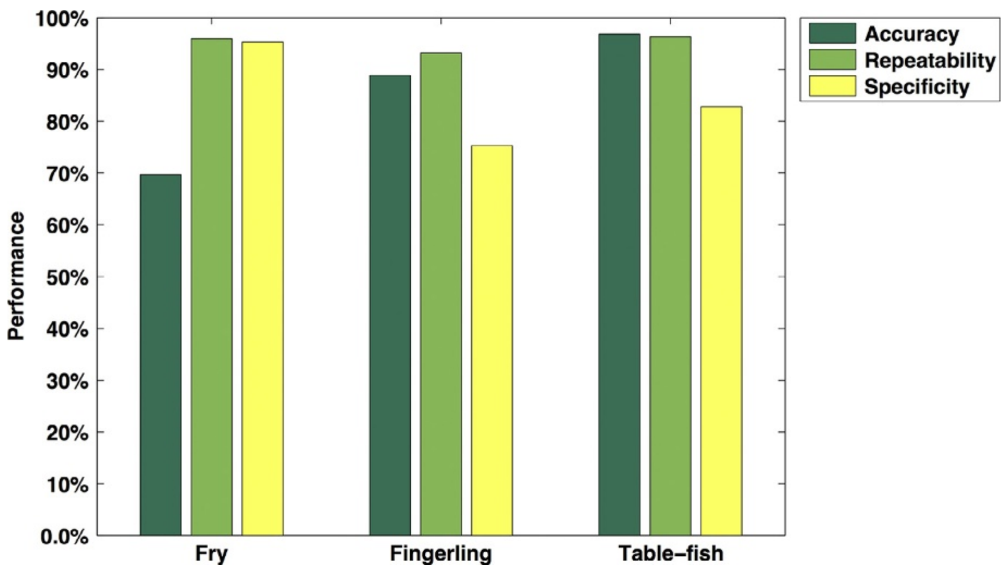

FIGURE 6

Accuracy, repeatability, and specificity performance when classifying fry, fingerling, and table-fish trout at three standard deviations using our statistical measuring system.

Table 10 Recall when Classifying Testing Sets at Three Standard Deviations

Testing as	1Sx (%)	2Sx (%)	3Sx (%)
Fry	67.00	64.50	56.70
Fingerling	86.33	68.35	92.55
Table-fish	92.00	52.00	100.00

Table 11 Precision when Classifying Testing Sets at Three Standard Deviations

Testing as	1Sx (%)	2Sx (%)	3Sx (%)
Fry	73.90	78.84	95.93
Fingerling	63.79	80.00	93.21
Table-fish	54.12	52.00	96.25

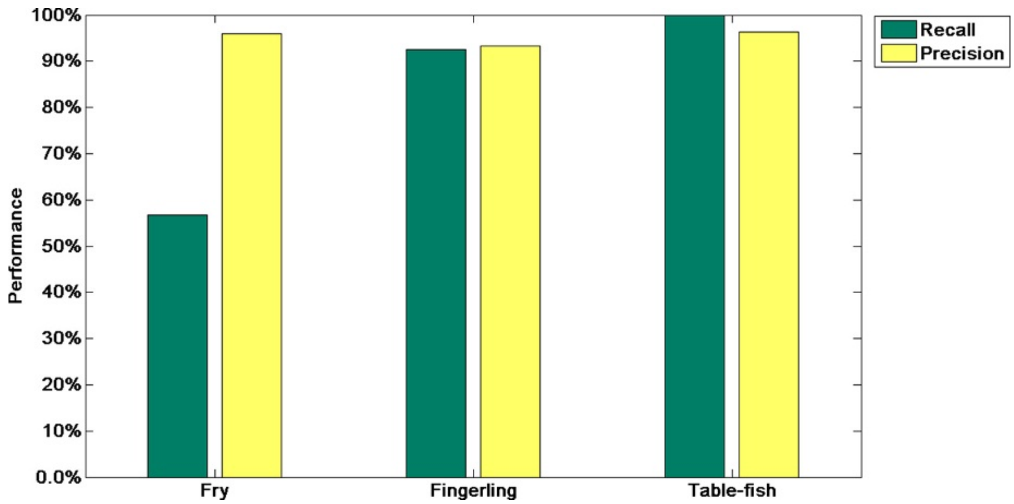

FIGURE 7

Recall-precision metrics when classifying fry, fingerling, and table-fish trout at three standard deviations using our statistical measuring system.

Furthermore, when classifying those testing lengths, we score a 100% recall and 96.25% precision when classifying table-fish trout at three standard deviations.

These experimental results are not only motivated, but also valuable evidences that indicate effectiveness in our classification system.

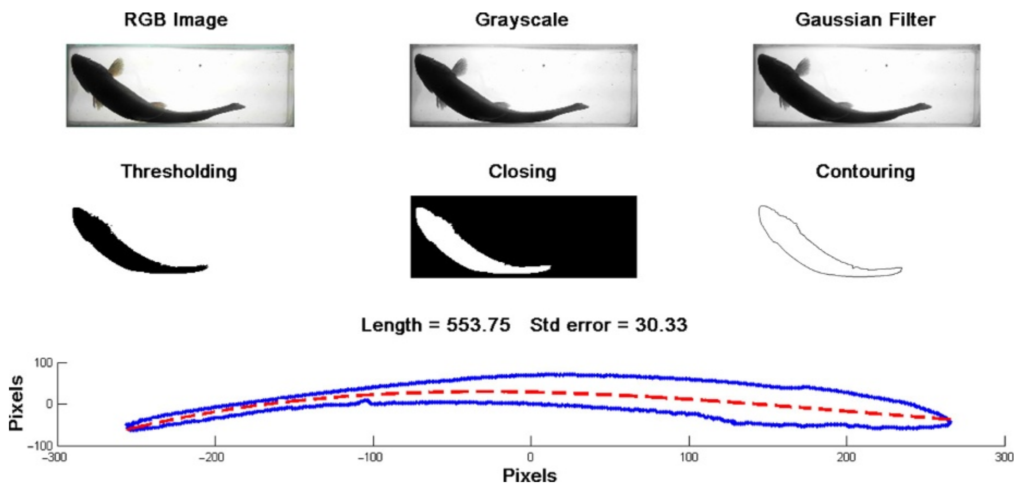

FIGURE 8

Processing a table-fish trout image for classification using our statistical measuring system.

6 CONCLUSIONS

In this article, we have robustly evaluated our statistical system to measure rainbow trout in farm using computer vision as observed in Figure 8. This novel technique [8] is a simple but effective statistical method, which has been evaluated in a small farm in central Mexico named *Rincon del Sol* [9].

For this research, we have designed and implemented a functional prototype to collect RGB trout images. This prototype includes canalization, illumination, and vision components that have been meticulously assembled. Also, we believe that this prototype could be easily integrated into a mechanical system to interconnect lined earth tanks in farms.

Our experimental results encourage our research as they have shown that our classification system is effective, where 95.93%, 93.21%, and 96.25% precisions are observed when classifying fry, fingerling, and table-fish trout, respectively.

It is important to observe that, although our statistical approach has been inspired to measure rainbow trout, this approach can be applied to other fishes grown in farms.

As part of our future work, we are integrating water flow and stereovision into our prototype to investigate two main issues: the light reflection into the water and the presence of turbulence. Our final aim is to implement an economical classification system for small farms.

ACKNOWLEDGMENTS

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Capítulo 4

A prototype to measure rainbow trout's length using image processing

En este capítulo se presenta el manuscrito que reporta el trabajo de investigación en la medición de la trucha arcoíris por procesamiento de imágenes digitales, el cual se envió para su revisión y posible publicación en la revista internacional *Aquacultural Engineering (ISSN: 0144-8609)* de Elsevier. Esta revista internacional tiene un factor de impacto 1.381 y se encuentra indexada en: Scopus, Science Direct, Mendeley, Evolve, Knovel, Reaxys y Clinical Key.

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Title	A prototype to measure rainbow trout's length using image processing
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Abstract

In rainbow trout farming, automatic measuring for classification is an open problem, when in most of small farms this work is done manually within a laborious process and achieving inaccurate measurements. In this paper we present state of the art results in rainbow trout's (Oncorhynchus mykiss) length estimation within a water flow using image processing. For this purpose, we have designed, implemented and evaluated a novel measuring prototype which allows the fish swimming through out its channel in order to be measured and classified, taking advantage of the rainbow trout's instinctive behaviour in swimming against the water flow. Our prototype is provided with a vision component which is able to detect and measure the rainbow trout online by capturing and processing downward-view images when the fish passes below the camera. A fish is detected into the system when it cross a control point defined for this purpose and to activate our measuring function. Based on our previous work, we are approximating a third order regression curve to the fish's body to estimated its length. In our experimental evaluation we are achieving 1.413 cm mean absolute error (MAE) when estimating rainbow trout's lengths. This is an encouraging result and it allows us to draw different venues for future work based on our experimental findings.

Keywords	Measuring fish prototype; rainbow trout; image processing

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A prototype to measure rainbow trout's length using image processing

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Abstract

In rainbow trout farming, automatic measuring for classification is an open problem, when in most of small farms this work is done manually within a laborious process and achieving inaccurate measurements. In this research we present state of the art results in rainbow trout (Oncorhynchus mykiss) length estimation within a water flow using image processing. For this purpose, we have designed, implemented and evaluated a novel measuring prototype which allows the fish to swim throughout its channel in order to be measured and classified, taking advantage of the rainbow trout instinctive behaviour in swimming against the water flow. Our prototype is provided with a vision component which is able to detect and measure the rainbow trout online by capturing and processing downward-view images when the fish passes below a camera. A fish is detected into the system when it crosses a control point, event that recalls our measuring process. To measure, we approximate a third order regression curve to the fish body to estimate its length. In our experimental evaluation we are achieving 1.413 cm mean absolute error (MAE) when estimating rainbow trout lengths. This is an encouraging result that allows us to draw different venues for future work based on our experimental findings.

Keywords: Measuring fish prototype, rainbow trout, image processing

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1. Introduction

Aquaculture is the farming of aquatic organisms in both coastal and inland waters that involves interventions in the rearing process to enhance production (FAO, 2016).

From last decades, aquaculture has increased and extended worldwide in both production and consumption of aquatic products, demanding from farmers better fish rearing processes for consumers who are expecting quality, freshness and authenticity on their products (Saberioon et al., 2016; Dowlati et al., 2012; Mathiassen et al., 2011).

Fish farming needs supervision to sort out the fish during different growth stages (fry, fingerling and table-fish) to avoid severe low growth, cannibalism and unfair competition; and also to provide required amount of food and medicine. This sorting process is done through certain characteristics, such as: size, gender, species, weight and shape to separate into consisting fish groups (Dowlati et al., 2012; Zion, 2012; Dowlati et al., 2012; Mathiassen et al., 2011).

The estimated fish length allows the farmer to infer the fish size and to sort out the specimen during their different growth stages. The fish size helps farmers to have better decisions about grading and harvesting. Besides, farmers can supervise growth rate and plan accurate feeding to avoid excess of food as it is one of the main water pollution contributors (Beddow and Ross, 1996).

Despite of the advance in technology (Northwest Marine Technology, 2016; VAKI, 2016), traditional manual methods are still used in small farms to estimate the fish length during their different growth stages. Indistinctly, those methods not only cause stress and physical damage to the fish, but also they are usually time-consuming, costly, laborious and invasive (Saberioon et al., 2016; Romero et al., 2015; Zion, 2012).

Because in a manual sorting, one fish at a time is extracted from the water to be visually inspected and measured. Based on this judgement, the farmer makes a decision, e.g. whether the fish needs to be changed to another pond or if it is ready for human consumption. Unfortunately, this visual measurement is not necessarily accurate (Romero et al., 2015; Shafry et al., 2012).

About fish farming in Mexico, rainbow trout (Oncorhynchus mykiss) is one of the most cultivated fish for feeding. Especially in high altitude states where the water's conditions such as low temperature and cleanness are suitable to rear this specimen (Romero et al., 2015; Montero, 2013). Furthermore, this fish is easily adapted to quite diverse environments, hence, it is possible to thrive it in pond's hatcheries (Frost et al., 2013; Staley and Mueller, 2000).

Researchers from different disciplines have been exploring possible approaches to improve productivity and profitability of fish rearing. Specifically, image processing has been showed as a non-invasive and economical method for fish length measurement, which is able to achieve promising results (Saberioon et al., 2016; Dowlati et al., 2012; Zion, 2012; Mathiassen et al., 2011). However, image processing has been mostly used on dead fish within the food industry and it has not been widely explored in aquaculture (Zion, 2012), this could be because of the natural challenge to measure accurately in an alive fish.

This research aim is to measure the rainbow trout length (table-size) within a water flow, indirectly manipulated by using image processing. For this reason, our experimentation was performed in a small rainbow trout farm named *Rincon del Sol*, which is located in Ocoyoacac, State of Mexico (Mexico), where as in most of small farms, earth ponds are used for rearing.

1.1. Related work

For decades, researchers have been advocated to investigate morphological characteristics such as fishes' length and mass from digital images. In this section we highlight key literature.

Zion et al. (1999) developed and tested an image process for discrimination between images of three different species: common carp fish, St. Peter's fish and grey mullet. This method is based on invariant moments coupled with geometric considerations from the fish head and tail. Downward-view fish images were acquired using their illuminated chamber, by placing each dead fish at the bottom of it. They reported correlation coefficients between manually measured lengths with estimated lengths as 0.950, 0.997 and 0.983 for fish common carp, St. Peter's fish and grey mullet, respectively.

In a later work, Zion et al. (2000) used (Zion et al., 1999) the same method to create what it is believed the first discrimination system among fish species in vivo. To do this, they created a concrete fish pond to take side view images when fish passed through an elongated narrow and transparent channel. Although, their fish species identification reached 100, 91 and 91% for grey mullet, carp and St. Peter's fish, respectively; a systematic fish training was required for the fish to know how to swim along the channel for identification. For this reason, it's thought that this is an impractical approach to be implemented in fish farms.

Odone et al. (2001) described a trainable system capable of determining fish weight from image measurements. They proposed a prototype that was installed as an automatic fish grading device at a fish farm, which was able to grade fish at a rate of three fish per second. From live trout sliding throughout a transparent channel, image measurements were taken from top and side views. They trained a support vector machine using linear and polynomial kernels to learn the relationship between fish shape and weight parameters. For their intended fish-weight estimation, they used 13 different shape measurements that are based on fish area, perimeter, length and width. Using a quadratic kernel and their 13 fish features, their best weight estimation scored a 3% absolute error with a 2% absolute standard deviation. They also noticed that fish area measurements were more accurate to estimate fish weights than fish length measurements, which are typically used in biology.

Karplus et al. (2003) created and tested three types of apparatus to induce guppy swimming throughout narrow channels using their positive phototactic and rheotactic innate response, to be inspected and sorted by a computer vision system. They obtain results of 96% and 100% in female and males, respectively, when leading them to a selected channel output.

White et al. (2006) created a computer vision machine (The CatchMeter) to identify and measure different species of dead fish. In this system, a fish is moved through a conveyor belt out, where digital images are captured to determine the fish orientation by using the invariant moments method. They obtained 100% accuracy in determining whether the fish is rounded or flat, with a standard deviation of 1.2 mm in length and a 99% successful classification among seven fishes.

Using stereo vision, Costa et al. (2006) proposed a submersible dual camera module connected to a portable water PC equipped with two frame grabbers. To obtain binary images, they used filtering and segmentation with a fixed threshold. Major length and circularity axis were analysed from images segments and those that fit into pre-established ranges where considered to belong to the fish. Then, landmark points in stereo image pairs were located for geometry calculation. Distances between key points were calculated by locating in 3D the fish boundary. A 5% fish-length estimation error from a single measurement of a fish model is reported.

In a comparative study of nine fish-size sorting methods using computer vision, Ibrahim and Sultana (2006) set up five complexity levels based on how fish is fed to their system's conveyor belt. They concluded that, even though, methods based on computer vision have shown aspiring prospects, their detailed analysis found no satisfactory of fish-size sorting techniques in terms of speed, accuracy and handling of complexities altogether. Therefore, they said that there is an opportunity to do further research on automatic fish-size sorting for industrial use.

Zion et al. (2007) introduced a technique to sort out common carp, St. Peter's fish and grey mullet. Side view fish images were acquired by a computer vision system while swimming through a narrow channel with their side to the camera at a relatively constant distance. To overcome water opaqueness, the channel is backlit by a series of fluorescent lights to generate high image contrast. Size- and orientation-invariant features are extracted from the fish silhouettes. Using Bayes classification in a laboratory prototype, an accuracy of 98.9%, 94.2% and 97.7% is achieved by grey mullet, St. Peter's fish and carp images, respectively.

Shafry et al. (2012) proposed a framework (FileDI) to measure the fish length using optical theory (Hsu, 2008) and images processing techniques that automatically measures dead fish length (Abdullah et al., 2009), by processing an input image to detect fish head and tail. This framework consists of five main stages: Pre-processing, bending ratio plot, corner factor calculation, fish length estimation from image and calculating the fish length. This framework was used to measure *R. Kanagurta* and *S. Crumenophthalmus* fish (twenty specimens each), using two types of camera, two types of illumination and three camera positions. Although, an overall results analysis was not presented in detail, they claimed a 95% accuracy for fish length measurement.

Torisawa et al. (2011) developed a simple method using direct linear transform and $Move - tr/3D^{TM}$ software to obtain three-dimensional measurements of cultured Pacific blue-fin tuna, which were freely swimming in a net cage. They believed that information obtained from stereo images could be useful for managing the growth of tuna during rearing, for that purpose they particularly estimated the fork length of individual fish. They tried to calculate the size of all recorded tuna in which they could distinguish the snouts and tail forks during monitoring. However, they were able to estimate fish length no farther than 5.5 m from the camera system. Then, they only could accurately estimate 99% sizes (106/107) of tuna recorded at that distance, with error ratios ($standard\, error/mean$) less than 5%.

Costa et al. (2013) created a methodological tool applicable to order farmed seabass by size, sex and skeletal anomalies by using elliptic Fourier analysis on digital images and partial least squares modelling. Their RGB-image processing includes seven steps: two-channels image transform: G and V; background value as the mean of G and V on the darker pixels (5%); Euclidean distances from the background value; elimination of the extremes (1%); rescaling; edging canny; and dilate (3) & fill filtering. The proposed techniques integration produced size estimation (in weight) with a better regression efficiency (r=0.9772) than the commonly used logarithmic measured body length (r=0.9443). The two partial least squares discriminant analysis models used to select sex and malformed fish also returned high discrimination efficiencies (82.05% and 88.21%, respectively).

Viazzi et al. (2015) tested and evaluated a computer vision technique that estimates the mass of dead jade perch fish, capturing a set of 120 images outside the water and extracting different features using single-factor regression on a fish area image without considering the fin tail. Their image processing consisted of four consecutive tasks: a) region of interest delimitation within a white-background-image, by locating a black painted square using an adapting threshold (Otsu, 1979) for each colour spectrums; b) fish segmentation, where they got binary images using adaptive thresholds. They considered the fish as the biggest connected object, and finally, the image was rotated using the angle between the x-axis and the mayor axis of the ellipse that had the same second moment as the region; c) tail fin removing, by extracting the fish contour from the binary image and computing Euclidean distances among contour points and the contour's centroid, the tail fin is considered the highest peak from the respective Euclidean distance plot; and d) shape feature extraction, from the binary image the fish body area, length and height are computed (no detail is provided). Regression analysis was used for fish mass estimation, which revealed a coefficient of determination (R^2) of 0.99. Also, when evaluating their data set, a mean relative error of $6\pm$ 3% was obtained when comparing the value measured by a weighing scale. Regarding measured lengths and heights, the error for length ranged from 0.2% to 2.8% with a mean error of $1.2 \pm 0.8\%$ and the height error ranged from 0.4 to 3.7% with a mean error of 1.5%.

Additionally, some commercial systems are available for fish length measuring, counting and weighting during rearing. Systems as *Fish Counter* from Vaky (VAKI, 2014) counts, weighs and sizes by fish gliding through channels and has a 99% accuracy in fish counting. The *Riverwatcher Fish Counter* (VAKI, 2016), is a submersible system able to measure fish length and swimming speed. For that purpose, a measuring component is placed where every fish in the river could pass, capturing side view images for fish length estimation. This system shows a precision of 98% and 95% for counting and measuring, respectively. Currently, the most complete commercial system is *AutoFish Sorting* from Northwest Marine Technology (2016), which is based on fish length estimation, automatically aligns, classifies and sorts. This system glides the fish through a ramp where upper view images are captured for fish length estimation using computer vision techniques, achieving a mean accuracy error of $1\,mm$ among total lengths.

1.2. Automatic classification problem

An automatic fish classification system during different growth stages is desired to improve fish harvest and profitability in farms. This system could help farmers to improve classification and harvesting. Ideally, this system should be able to extract individual fish features, such as: length, mass, weight, sex and skin colour from one fish at a time (Karplus et al., 2003; Zion, 2012).

Different technology can be use for an automatic classification. However, this research is mainly interested in investigating an image processing approach. Thus, this problem concerns to have a non-invasive technique to make specimens to cross throughout a system for individual image processing analysis. To do this, we visualise three main sequential steps:

a) **Fish alignment.** We need to face some problems concerning fish behaviour in rearing ponds. Because, specimens stay in dense shoals that cause occlusion. Then, we need to divide and space out the shoal to make every fish pass across a channel. This step is considered essential to get an automatic classification system based on accurate fish measurements.

b) **Fish analysis.** In this step we need to establish the number of fish classes and their features that are related to the problem. Then, in terms of that, it's defined appropriate image acquisition conditions and image processing techniques.

c) **Fish sorting.** This step includes a physical separation based on the number of classes established in the previous step.

In a previous work, we developed a prototype to classify rainbow trout in fry, fingerling and table-fish sizes. To do this, a pyramid prototype to capture downward-view digital images was constructed. From captured images, the fish body silhouette is extracted and it is used to approximate a third order regression curve to estimate the fish length (Romero et al., 2015).

Then, based on such experience and interest, we continue our research by designing, developing and evaluating a prototype based on a passive technique to make specimens to cross throughout a channel. This is done by using the rainbow trout instinctive behaviour in swimming against a water flow, where downward-view images are taken and analysed for length estimation. By doing this, we believed that it is a measuring non-invasive and efficient technique.

2. Materials and methods

This section contains materials and methods used for this research. Subsection 2.1 depicts our measuring prototype evolution. Subsection 2.2 presents our measuring prototype. Subsection 2.3 shows our prototype's installation. Subsection 2.4 describes our experimental sample. Subsection 2.5 details our image processing for fish detection and measuring. Finally, Subsection 2.6 indicates our measurement analysis.

2.1. Protype's background

Our measuring prototype has been evolving since 2013 towards a Bsc Thesis (Miranda, 2014), where a pyramidal prototype was proposed to capture upward view image to classify the rainbow trout based on estimated fish length (Romero et al., 2015, 2014), until the prototype we introduce here. Figure 1 depicts our measuring prototype evolution.

2.2. Measuring prototype

In fish hatcheries, the pond's shape and hydraulic conditions influence the distribution, position, growth, metabolism and behaviour of rearing fish (Ross et al., 1995; Duarte et al., 2011; Staley and Mueller, 2000). Taking this into consideration and attending problems related to this research (see Subsection 1.2), we have designed a four-level prototype that can be set aside a fish earth pound, which receives the pond natural water flow and avoids occlusion as one fish is fed at a time (see Figures 2 and 3). Additionally, to promote the fish displacement into the prototype's channel, we are using

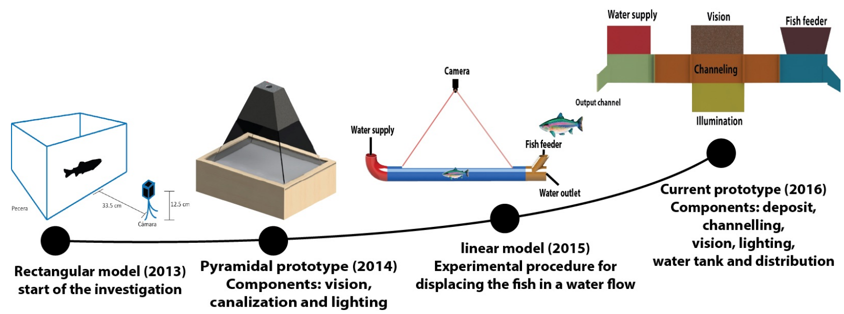

Figure 1: Evolution of the proposed prototype to measure the rainbow trout's length.

their instinctive behaviour in swimming against a water flow (Frost et al., 2013; Woynarovich et al., 2011; Blanco, 1993).

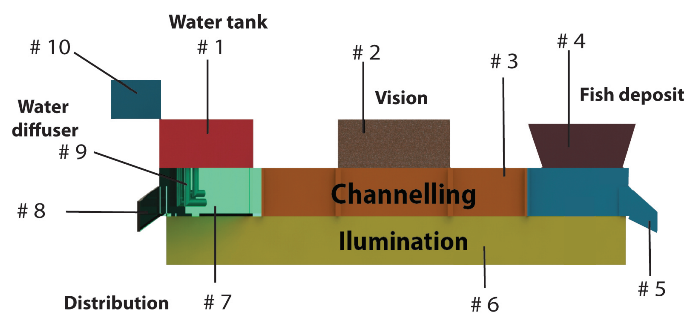

Figure 2: Components of the measuring prototype to estimate the rainbow trout's length (lateral view): Water supply (#1), vision (#2), channelling (#3), Fish feeder (#4), water outlet (#5), illumination (#6), distribution (#7), outlet channel (#8), water diffuser (#9) and Water switcher (#10).

Seven components integrates our prototype: water switcher, water supply, channelling, illumination, fish deposit, distribution and vision. These components are described below.

2.2.1. Water switcher

As we mentioned before, the rainbow trout is a fish that swims upstream and downstream in a water flow (Staley and Mueller, 2000). Taking this into consideration, we thought that an intermittent water flow could promote fish displacement upstream, this is done by a water switcher component (#10 in Figure 2) installed in the fourth level of our prototype. This a $20x20x20\,cm$

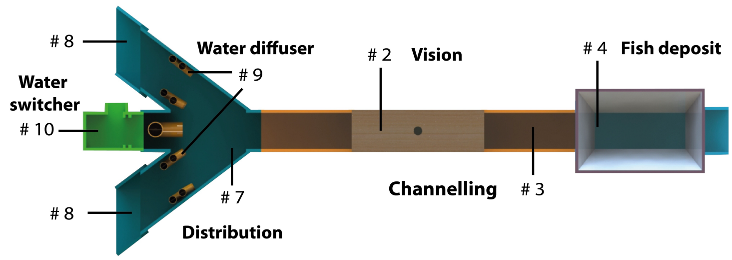

Figure 3: Upward view of our prototype to estimate the rainbow trout's length. The componentes are vision (#2), channelling (#3), fish deposit (#4), distribution (#7), water diffuser (#9) and water switcher (#10).

component located in the fourth level of the measuring prototype. Two floodgates have been included to regulate the water flow into the prototype by opening and closing them manually.

2.2.2. Water supply

This component collects and distributes the water flow into the channelling component, by means of a water tank and five water diffuser arrays.

The water tank (#1 in Figure 2), is located in the third level of the measuring prototype. It is a trapezoidal shape with a 1452.5 cm^2 base area and height decided by (Davila, 1974).

$$Hight\ water\ tank = \left(\frac{Q_E}{8A_1 * C_d\sqrt{2g} + A_2 * C_d\sqrt{2g}} \right)^2 \qquad (1)$$

Where Q_E is the inlet water flow ($0.000852\, m^3/s$, estimated with the volumetric method), A_1 is the central diffuser area ($0.000506\, m$), A_2 is a lateral diffuser area ($0.0020\, m$), C_d is the spending ratio (≈ 0.6) and g is the gravity constant ($9.81\, m/s^2$). With those values, Equation 1 gives us a water flow height of $0.0075\, m$, which remains constant for the water tank inlet and outlet parameters. We decide a water tank high of 15 cm to handle a higher inlet water flow Q_E, hence the water tank capacity is $0.02178\, m^3$.

The five water diffuser arrays, located at the bottom of the water tank (#9 in Figure 2), are thought to generate a water flow into the prototype. This is possible by feeding water at different heights ($8, 11\, and\, 11.5cm$) along 'L' shape pipes, placed on every side of the distribution component's walls and at the channel's centre. Lateral and central pipes are 2.54 cm and 5.08 cm, respectively.

2.2.3. Channelling component

The channelling component is located in the second level of the prototype (#3 in Figure 2) and directs the water flow in a linear path up to an outlet duct (#5 in Figure 2). This is rectangular chamber and it has the following dimensions $0.15x0.14x1\,m$ in height, width and length, respectively.

The main function for this component is to lead the rainbow trout during their swimming upstream from the fish deposit to an exit in the distribution component.

2.2.4. Illumination component

Illumination plays an important role in the overall efficiency and accuracy of any image processing system, because it greatly affects the quality of captured images (Gonzalez and Woods, 2008). An appropriate lighting system can reduce the effect of reflection, shadow and some noise, thereby reducing the required time for image processing (Szeliski, 2011). The aspects to be considered in an illumination system are location, lamp type and colour quality (Saberioon et al., 2016).

Then, an illumination component is integrated in the prototype and it is located at the first level (#6 in Figure 2). In fact, this is a source of diffuse light at the bottom of the channelling component that increases contrast in the acquired digital image, highlighting the rainbow trout body. The light source height was defined experimentally (Romero et al., 2015) and it consists of four $90\,lm$ lamps and they are allocated in rectangular base with a dimension of $1.8x0.14x0.16\,m$ in height, width and length, respectively.

2.2.5. Fish deposit

The fish deposit component, located in the third level, was designed for the rainbow trout welfare by easily setting the fish down into the prototype's channel (#4 in Figure 2).

The fish deposit is trapezoidal shape and its dimensions are $40x30\,cm$ at top and $30x15\,cm$ at the bottom.

2.2.6. Distribution component

As we mentioned before, this research is based on the rainbow trout instinctive behaviour in swimming against the current. Hence, an upstream water flow permits the specimen to cross the channelling component leading it to an exit.

Therefore, the distribution component is integrated as the exit part of the prototype, that is located in the second level and contains two exits (#7 in Figure 2). This component has a W shape, providing two outputs for fish separation (#8 in Figure 3).

2.2.7. Vision component

This component is integrated into the prototype to capture and process digital images by the time the rainbow trout pass through its channel.

The capturing process is performed through a digital camera physically located in the prototype's third level at the central part of the channelling component (#2 in Figure 2). This is a 2D LifeCam Studio camera able to capture RGB images with a maximum resolution of 1920x1080 pixels, 30 fps Microsoft (2014).

That digital camera is situated over a physical region that we called *region of interest*, which is a $40x12\,cm$ area at the base of the channel retro-illuminated by the illumination component.

Taking into account the region of interest size and the geometry based on a projection camera model (Pears et al., 2012; Szeliski, 2011), the digital camera is $32\,cm$ high from the channelling component base, allowing a field of view widely enough to capture the $40\,cm$ region of interest length (see Figure 4).

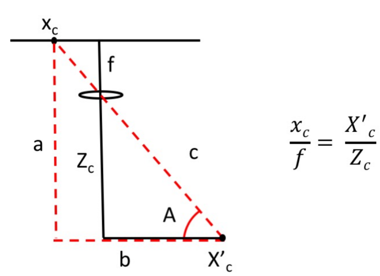

Figure 4: Geometry based on a projection camera model. Where x_c is the position of a point in the camera's image plane, f is the distance of the image plane to the camera centre (focal length), X_c is a 3D world point through the camera centre and Z_c is the direction of the principal axis of the lens that encodes depth from the camera.

Additionally, limiting the image section to be processed, two reference walls (made of opaque glass) were allocated inside the channelling component along the region of interest at 80^o, which was calculated using basic trigonometry (see Figure 4):

$$Cos\,A = \frac{b}{c} \tag{2}$$

Where $b = 31.385\,cm$ and $c = 32.9074\,cm$, considering a $3.85\,mm$ focal length and a $4.8\,mm$ size sensor.

The vision component has a logical part for image processing, which is the essence for this research. Therefore, two main functions were programmed in Matlab for fish detection and measuring on captured images, those functions are detailed in Section 2.5.

2.3. Prototype setup

Two steps are required to set up our measuring prototype in the experimental farm to measure a rainbow trout specimen.

a) **Prototype assembly**
The experimental farm has a linear arrangement of grounds ponds in levels, which allows to feed a water flow in cascade among them. Then, the measuring prototype was placed between two consecutive ponds at convenient distances to provide it with electricity and water. Additionally, a personal computer was installed over the measuring prototype for image acquisition.
To branch off the water flow towards the measuring prototype, an hydraulic installation was required, by connecting an array of PVC ducts from a pond water fall to the prototype's water switcher as it is illustrated in Figure 5.

Figure 5: Prototype to measure rainbow trout's length installed in situ.

b) **Water flow measuring**
The water flow fed into the prototype was measured using the volumetric method (Woynarovich et al., 2011), which measures the required time to

Fish #	length (cm)	Width (cm)	Thickness (cm)
1	25.00	6.00	2.80
2	28.00	6.50	3.00
3	28.50	6.70	3.00
4	27.50	5.90	2.70
5	26.50	6.50	2.90
6	28.00	6.30	2.90
7	27.00	6.00	2.80
8	25.70	5.50	2.50
9	26.30	6.00	2.80
10	26.00	5.70	2.50
Mean	26.85	6.11	2.79

Table 1: Summary data set obtained from experiments with our experimental procedure.

fill a container of known volume. Using this method, a $0.851\,L/s$ water flow was recorded causing a water depth of $2.5\,cm$ along the channelling component. The water flow speed was also estimated by sampling the required time for an object to cross along the prototype's channel, obtaining a speed of $14.004\,m/s$.

2.4. Experimental sample

For this experiment ten table-size rainbow trout were used. These specimens were visually selected by the farmer in the experimental farm. After that, every specimen was firstly measured by the prototype. Once a fish reached an exit, their length, width and thickness were manually measured using a Vernier scale (see Table 1).

An indirect manipulation was performed by feeding one rainbow trout at the time into the fish deposit. Then, an intermittent water flow was created into the channel, this was done by opening and closing the water switcher floodgates at intervals of $1.6\,s$. Then, a downward-view video recording was obtained for every fish passing through the prototype, so that it gives ten videos, which length corresponds to the fish swimming time to exit the prototype. These videos were recorded using a Matlab script based on its image acquisition toolbox. This is the raw data used for our image processing approach.

2.5. Image processing

This section describes our image processing approach for fish detection and measuring.

2.5.1. Fish detection

For fish detection into the prototype it was defined named *region of interest*, which in fact is the covered area within the camera's field of view at the channel's base high. As observed in Figure 6, two areas have been defined to assist this process: Start indicator and End indicator.

Figure 6: The three areas that integrated in the prototype's region of interest that help to detect a fish into the channel.

The complete rainbow trout detection process is shown in Figure 7.

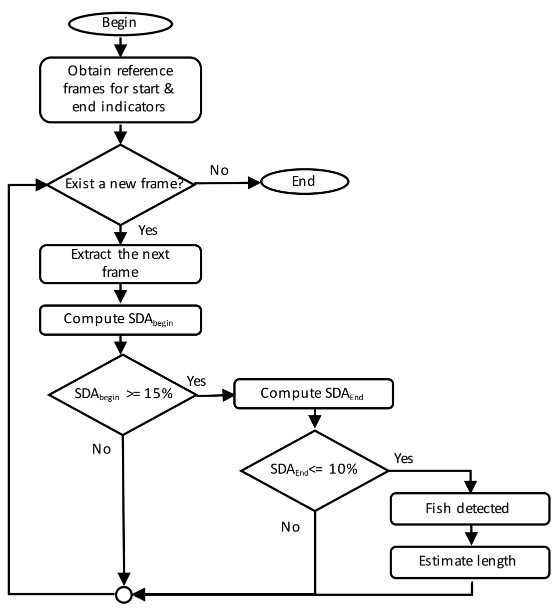

Figure 7: Process to detect a rainbow trout into a captured image while it crosses the prototype's region of interest.

First a reference frame is captured, which is an image of the region of interest containing only the water flow, which is compared against every new captured frame by computing the square difference addition (SDA):

$$\frac{\sum_{i=1}^{N}(Img1[i] - Img2[i])^2}{N} \tag{3}$$

Where $Img1$ and $Img2$ are $[length\, x\, width]$ images, represented as row vectors, and $N = length * width$.

Then, given a new frame, the start indicator SDA is calculated. If (SDA_{begin}) is greater than or equal to 15%, the end indicator SDA is obtained (SDA_{end}) and a fish is detected, if (SDA_{end}) is less than or equal to 10%. Hence, the fish measuring function is executed.

Thresholds 15% and 10% were obtained experimentally by computing the mean $\bar{x}$ and standard deviation $S_{\bar{x}}$ from ten rainbow tout head images. Then, threshold for the standard indicator area equals $\bar{x} + 2S_{\bar{x}}$, while threshold for the end indicator area equals $\bar{x} - 2S_{\bar{x}}$

Note that fish counting is possible as it equals the number of detected fish using this approach.

2.5.2. *Fish measuring*

For fish measuring, standard image processing algorithms have been used to get the fish body silhouette (Gonzalez and Woods, 2008; Szeliski, 2011), which is given to our statistical approach to estimate the fish length (Romero et al., 2015). The detailed process is as follows.

a) Convert the input RGB image to grayscale, using a standard weighted addition of its components: $0.2989 * R + 0.5870 * G + 0.1140 * B$.
b) A binary image is obtained using a 0.7058 threshold, which was experimentally calculated based on a rainbow trout histogram. Taking into account that the histogram is bimodal, where the first mode is the fish body.
c) The rainbow trout body is emphasized by using three morphological operations: dilating, opening and closing (Gonzalez and Woods, 2008), which operation masks are shown in Figure 8.
d) Connected components are labeled using a N_8 neighbourhood (Szeliski, 2011) and the second largest connected component is considered as the fish body silhouette.

$$\begin{matrix} 1 & 1 & 1 & 1 & 1 \end{matrix} \qquad \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix} \qquad \begin{matrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{matrix}$$

(a) (b) (c)

Figure 8: Operation masks to emphasize the rainbow trout's body, a) *dilating*, b) *opening* and c)*closing*.

e) Taking the fish body silhouette as an (x, y) points set, a fish length is estimated by interpolating a third order regression curve (Romero et al., 2015).

f) To convert the regression curve units from pixels to millimetres, the camera's model intrinsic and extrinsic parameters are considered (Pears et al., 2012; Zhang, 2000):

$$\begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} = \lambda \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \begin{bmatrix} \alpha_x & s & x_0 \\ 0 & \alpha_y & y_0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} r_1 \\ r_2 \\ t \end{bmatrix}^{-1} \tag{4}$$

Where $[X, Y, 1]$ are coordinate points in millimetres; $[x, y, 1]$ are coordinate points in pixels; λ is an arbitrary scale factor; $[r_1, r_2, t]$ are the extrinsic parameters, rotation and translation, which relates the world coordinates system to the camera's coordinate system; (x_0, y_0) are the origin point coordinates from a reference image; (α_x, α_y) are scale factors according to the reference image for the x and y axes; and s is the skew between the two images axes.

g) Finally, the rainbow trout length is computing by adding the Euclidean distance among the set of points within the regression curve.

2.6. Measurement analysis

According to Lehmann and Casella (1998), root mean square error, mean absolute error and mean relative error are computed for length measurement analysis.

The root mean square error (RMSE) represents the sample standard deviation of the differences between estimated values and measured values:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} [EL_i - ML_i]^2}{N}} \tag{5}$$

The mean absolute error (MAE) shows how close forecasts or predictions are to eventual outcomes:

$$MAE = \frac{\sum_{i=1}^{N} |EL_i - ML_i|}{N} \tag{6}$$

The mean relative error (MRE) indicates how large the length error is in relation to the length measured.

$$MRE = \frac{\sum_{i=1}^{N} \left(\frac{|EL_i - ML_i|}{ML_i} \right)}{N} \tag{7}$$

Where EL_i is the *i-th* fish estimated length; ML_i is the *i-th* manual fish measured length; and N is the number of estimated lengths.

3. Results and discussion

As mentioned in Section 2.4, one video per fish was recorded when it passes throughout the prototype. Then, those videos were analysed frame by frame from the fish entrance to exit to measure every fish detected (see Section 2.5). As indicated by Armstrong and Collopy (1992), a performance evaluation was done by computing mean square, mean absolute and mean relative errors using equations 5, 6 and 7, respectively.

From this experiment, two main results are obtained, fish detection and measuring.

To evaluate our fish detection process (Section 2.5.1), we visually counted the number of times that a fish crosses throughout the region of interest marking upstream and downstream swimming. A total of forty-six fish swimming were counted, each one with different number of images, implying different swimming speed. Then, these forty-six fish swimming were processed by our fish detection approach, from which, in 244 images a rainbow trout was detected and measured (Section 2.5.2), an illustration is shown in Figure 9. Table 2 summarises our fish detection results, where it is observed that in one occasion specimens eight and nine were not detected.

Comparing our manual counting against our fish detection module results, we are achieving a weighted mean of 96.7% successful fish detection, from that comparison we also observed that our fish detection module is robust in detecting a fish regardless its swimming orientation (downstream and upstream).

Fish #	Swim	Orientation	# Images	Exit taken
1	us		3	No
	ds		11	
2	us		5	Yes
3	us		2	No
	ds		11	
	us		5	
4	us		2	Yes
	ds		1	
	us		2	
	ds		6	
	us		2	
5	us		1	No
	ds		8	
	us		2	
	ds		4	
	us		3	
	ds		19	
	us		9	
	ds		18	
6	us		5	Yes
	ds		6	
	us		1	
7	us		2	Yes
8	us		3	No
	ds		17	
	us		2	
	ds		2	
	us		2	
	ds		2	
	us		12	
	ds		Not detected	
	us		1	
	ds		2	
	us		1	
	ds		10	
9	us		1	No
	ds		Not detected	
	us		3	
	ds		3	
10	us		2	No
	ds		6	
	us		3	
	ds		7	
	us		2	
	ds		6	
	us		5	
	ds		24	

Table 2: Summary of experimental data set highlighting the number of times that a rainbow trout pass through the region of interest, upstream (us) and downstream (ds). Note some cases where the fish is upstream oriented, although it is swimming downstream.

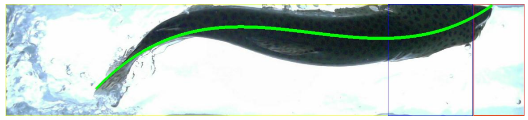

Figure 9: An illustration when a rainbow trout is detected and measured by our system. In this figure one can note its length depicted by a green line and also the start and end indicators.

Our experimental results for rainbow trout length estimation into a water flow are summarised in Table 3, where a $1.413\,cm$ mean absolute error and a 5.206% mean relative error are observed. Although, this performance is comparable with the state of the art, some large errors are observed and now we discuss two main causes:

a) *Freedom of movement:* Because of the channel's width (#3 in Figure 2) and the extreme rainbow trout's flexibility, its body can be freely contracted. This contraction occludes part of the fish body, then, the adjusted regression curve does not consider the complete body as we can see in Figure 10.

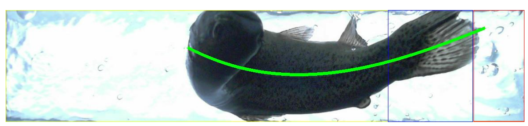

Figure 10: A sample when the rainbow trout's body is contracted.

b) *Trade off between water level and lighting:* We observed that a high water level reduces contrast between the rainbow trout's body and the illuminated channels floor (#3 in Figure 2), causing that the fish body could not be detected completely, particularly the trout's caudal fin as shown in Figure 11.

Figure 11: A sample when the fish body could not be detected completely due to high contrast.

Additionally, from this experimental research, a relevant discussion point is the channelling component in our prototype's design. Because of its width

Fish #	R.L. (cm)	E.L. (cm)	Mean	Grand Mean	RMSE (cm)	Mean RMSE (cm)	MAE (cm)	Mean MAE (cm)	MRE (%)	Mean MRE (%)
1	25.0	3	24.965	24.532	0.453	0.692	0.412	0.656	0.016	2.624
		11	24.100		0.931		0.900		0.036	
2	28.0	5	28.850	28.850	1.410	1.410	1.340	1.340	0.048	4.786
3	28.5	2	28.809	25.853	0.346	3.348	0.309	2.853	0.011	10.010
		11	27.934		0.875		0.566		0.020	
		5	20.816		8.824		7.684		0.270	
4	27.5	2	27.119	25.430	0.387	2.155	0.381	2.070	0.014	7.530
		1	20.769		6.731		6.731		0.245	
		2	26.005		1.872		1.496		0.054	
		6	26.723		0.780		0.777		0.028	
		2	26.537		1.006		0.964		0.035	
5	26.5	2	28.376	26.978	1.776	1.039	1.776	0.898	0.067	3.370
		8	26.723		1.241		1.045		0.039	
		2	27.007		0.437		0.407		0.015	
		4	26.299		0.411		0.363		0.014	
		3	27.162		1.240		0.844		0.032	
		19	26.739		0.919		0.803		0.030	
		9	27.696		1.280		1.096		0.041	
		18	25.819		1.011		0.847		0.032	
6	28.0	5	28.533	27.794	0.623	1.215	0.533	0.985	0.019	3.520
		6	26.462		2.635		2.034		0.073	
		1	28.388		0.388		0.388		0.014	
7	27.0	2	28.782	28.782	1.902	1.902	1.782	1.782	0.066	6.600
8	25.7	3	26.490	25.489	0.928	1.179	0.790	1.041	0.031	4.050
		17	24.986		1.072		0.988		0.038	
		2	27.133		2.304		1.805		0.070	
		2	25.574		0.254		0.221		0.009	
		2	27.047		1.527		1.347		0.052	
		2	25.171		0.576		0.529		0.021	
		12	25.558		0.632		0.462		0.018	
		1	26.070		0.370		0.370		0.014	
		2	23.228		2.490		2.472		0.096	
		1	25.792		0.092		0.092		0.004	
		10	23.330		2.721		2.370		0.092	
9	26.3	1	27.494	25.640	1.194	1.885	1.194	1.578	0.045	6.000
		3	23.765		3.309		2.535		0.096	
		3	25.661		1.151		1.004		0.038	
10	26.0	2	25.856	25.391	0.5759	1.068	0.558	0.929	0.021	3.570
		6	25.068		0.9884		0.932		0.036	
		3	25.848		0.7709		0.758		0.029	
		7	23.092		3.5497		2.946		0.113	
		2	26.064		0.2081		0.198		0.008	
		6	25.687		0.8003		0.590		0.023	
		5	26.228		0.6895		0.561		0.022	
		24	25.285		0.9623		0.889		0.034	
					Mean	1.589		1.413		5.206

Table 3: Estimated lengths summary with respective estimation errors when using our measuring prototype.

and to be positioned without any slope, the fish can freely swim along the channel and it is able to change its swimming direction (downstream and upstream). Although, our measuring prototype has been proved robust in estimating the rainbow trout's length in both directions, we are expecting the fish to be detected and measured once. Furthermore, such a freedom to swim upstream or downstream into the prototype's channel could avoid the fish to exit it. From our ten rainbow trout specimens only four got an exit channel by itself, the rest were taken out manually.

It is also important to control the fish orientation and position when passing across the channel, because the caudal fin is absolutely thin that if it is parallel to the camera, the caudal will be visualised as a line and it will be lost when the image is processed.

Above all, we found that our measuring prototype is suitable for fish detection and to estimate a fish length in presence of different fish orientations and positions when swimming into water flow.

4. Conclusions

In this document, we have presented state of the art results in rainbow trout's length estimation within a water flow using image processing.

For that purpose, we have designed, implemented and evaluated a novel prototype, which is taking advantage of the rainbow trout's swimming against the water flow to measure it. An essential part of this prototype is the vision component, which based on downward-view images to detect when a fish crosses a pre-established control point. Then, a third order regression curve is approximated to the fish's silhouette to estimate its length.

So far, our experimental results are scoring a 1.413 cm mean absolute error (MAE) using our novel prototype to measure the rainbow trout's length. This is an encouraging preliminary result that is comparable with the state of the art and it is useful to draw different venues for future work.

Acknowledgements

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Appendix A. Alternate prototypes

In this section we present our alternative prototypes to measure rainbow trout's length in a water flow.

Prototype A

The first prototype, shown in Figure A.12, consists of the following components: fish tank inlet, channelling, reducer, output channel, water diffusers, gate, vision, illumination. The water diffuser component supplies water and generates flow inside of the prototype. The fish is fed inside the inlet fish tank, which has a water flow. The fish is directed throughout a reducer to permit only one fish at a time to pass across the channelling component. The vision component measures a fish length in the field of view of the camera and switches the gate according to the length. Only two output channels are considered in this prototype.

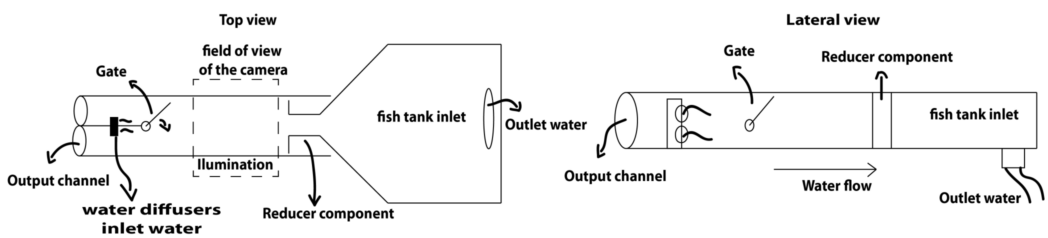

Figure A.12: First prototype to measure rainbow trout's length using image processing. We thought the integration of two output channels only.

Prototype B

The second prototype, shown in Figure A.13, consists of similar components and functionality as Prototype A, but it has two differences. The first difference is that it could have more than two gates and output channels. The second difference is the position of gates and output channels, which in this case are lateral side, intended to integrate two or more output channels.

Prototype C

The third prototype, shown in Figure A.14, is an immerse system into the rearing fish pond. This prototype consists of a flexible mesh, gate, containers, channelling and a vision component. For this prototype, a farmer needs to bury away the fish toward a pond corner with a flexible mesh, then, the fish is expected to swim across the channelling component. The vision component captures images for fish length estimation. Based on the fish length, a gate

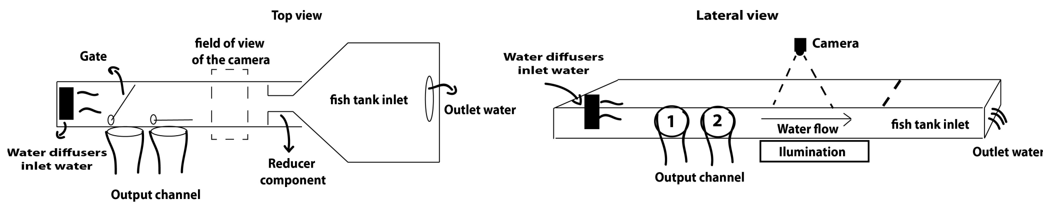

Figure A.13: Second prototype to measure rainbow trout's length using image processing. This prototype explores the integration of two or more output channels.

is switched to the corresponding container. Note that this proposal needs to be water proof.

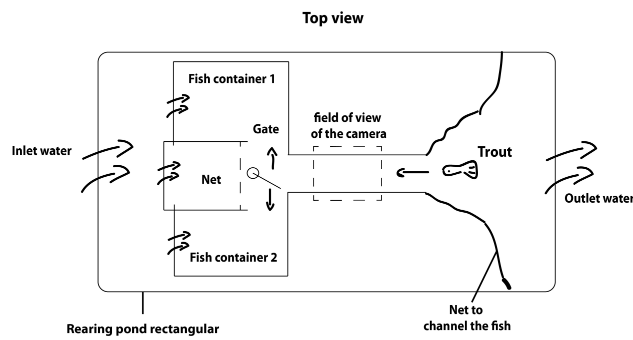

Figure A.14: Third prototype to measure rainbow trout's length using image processing. This prototype explores an immerse system into the rearing pond.

Prototype D

A fourth prototype, shown in Figure A.15, consists of a system that glides across a channel the fish to measure its length. Components of this prototype are: fish tank, channelling, vision, gate and output channel. The fish is fed into the fish tank where one by one is glided across the channelling component. The vision component capture images and estimate the fish length. The gate will be positioned based on the decision of the vision component and the fish enter in the corresponding container. In this system the fish tank is positioned at a height h above the ground and does not consider the rainbow trout to swim against a water flow.

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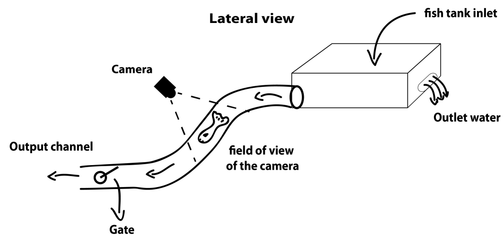

Figure A.15: Fourth prototype to measure the rainbow trout's length. This system proposes to glide the fish across a channel.

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Capítulo 5

Conclusiones y trabajo futuro

Este capítulo presenta los resultados obtenidos en esta investigación, la cual consistió en diseñar, construir y evaluar un prototipo para medir la longitud de la trucha arcoíris dentro de un flujo de agua. Además, se establece el trabajo futuro a seguir en la investigación.

5.1. Conclusiones

En esta tesis se ha propuesto un prototipo para estimar la longitud de la trucha arcoíris dentro de un flujo de agua usando procesamiento de imágenes digitales y tomando ventaja de su instinto de nado contra corriente. Para esto, se diseñó y construyó un modelo físico para la captura en línea de imágenes digitales de peces vivos, así como el software requerido para detectar y medir a los especímenes. Debido a esto, se puede concluir que se ha cumplido el objetivo general propuesto para esta tesis.

Por otro lado, las características de diseño del prototipo propuesto: a) forma lineal rectangular, b) dimensiones rectangulares $15x14x180\,cm$, c) flujo de agua ($0.851\,L/s$), d) altura de agua ($2\,cm$) y e) intermitencia del flujo de agua ($1.6\,s$), motivaron el nado contra corriente del pez. En este desplazamiento se obtuvieron imágenes de vista superior de una sección fija dentro del componente de canalización, con las cuales fue posible estimar la longitud del pez de talla adulta usando procesamiento de imágenes digitales. Con lo cual se cumple la meta de ingeniería postulada para esta tesis.

Para el desarrollo de esta investigación se propusieron cinco prototipos para desplazar la trucha arcoíris dentro de un flujo de agua (Ver Anexo A, Capítulo 4), de los cuales se eligió el diseño documentado en el Capítulo 4 de esta tesis.

Este diseño fue propuesto con base en las características físicas de la trucha arcoíris de talla adulta, específicamente: el largo, ancho y tonalidad de su cuerpo, así como las características hidráulicas y el caudal medido *in situ* (ver Sección 2.1, Capítulo 4). Además, esta propuesta buscó desplazar al pez dentro de un flujo de agua tomando como referencia su instinto natural de nado contracorriente.

El prototipo desarrollado consta de siete componentes: alimentador de peces, iluminación, visión, distribución, canalización; así como, caja de intermitencia y difusor de agua. La caja de intermitencia genera un flujo de agua intermitente dentro del prototipo. El difusor de agua almacena el agua y la suministra en el componente de distribución de forma directa. El componente de canalización permite al pez nadar contra corriente dentro del flujo de agua generado. El componente de visión permite capturar imágenes de vista superior en una región física dentro del componente de canalización (región de interés). El componente de iluminación retro-ilumina la región de interés para la ayuda de la captura de imágenes. El alimentador de peces permite introducir a los especímenes dentro del canal, permitiéndoles avanzar a contracorriente.

El prototipo desarrollado se evaluó experimentalmente *in situ* realizando lo siguiente: (1) se generó un flujo de agua dentro del prototipo, alimentando agua dentro de la caja de intermitencia, la cual es introducida al canal a través del difusor de agua. (2) se inició la captura de imágenes, obteniendo imágenes de forma consecutiva de la región de interés dentro del componente de canalización. (3) Se extrajo un peces del tanque de crianza de forma indirecta y se depositó en el tanque de peces dentro del prototipo. (4) Se generó un flujo intermitente dentro del prototipo usando la caja de intermitencia, para permitir al pez avanzar a contra corriente. (5) Una vez que el pez sale del prototipo a través de alguno de los dos canales de salida, se detiene la captura de imágenes en el componente de visión. Este proceso se repitió para el conjunto experimental, obteniendo 10 videos de peces que se desplazan a contracorriente.

El prototipo propuesto permite desplazar al pez dentro de un flujo de agua, utilizando el instinto natural de nado contra corriente de la trucha arcoíris. Sin embargo, la evaluación final de campo demostró que el pez puede invertir su orientación para nadar con la corriente o ser arrastrado por esta. Esto nos indicó, que el comportamiento del pez no es controlable.

Utilizando los módulos de procesamiento de imágenes propuestos (ver Sección 2.4, Capítulo 4) se procesaron los videos capturados en la experimentación fuera de línea para evaluar la medición de la trucha arcoíris dentro de un flujo de agua. La detección exitosa de peces dentro del prototipo de medición alcanza una precisión de 96.7 % y se ha mostrado robusta a cambios en la orientación de nado del pez dentro del canal. Por otra parte, se obtuvo un error cuadrático medio de 1.413 cm y una gran media del error absoluto de 5.206 % en todas las estimaciones de longitud realizadas (ver Sección 3, Capítulo 4), los cuales son valores comparables a lo reportado en la literatura.

5.2. Trabajo futuro

Finalmente, en esta sección se presenta una visión sobre posibles líneas de investigación de trabajo futuro en el problema de medición automática de la trucha arcoíris, a partir del alcance de esta tesis.

Debido a los problemas encontrados al permitir libertad de movimiento del pez dentro del prototipo, se recomienda rediseñar la forma del componente de canalización. Para esto, se sugiere experimentar una rampa de deslizamiento en forma de 'V' en lugar del canal rectangular, con lo cual se espera limitar el movimiento de nado del pez, alineándolo dentro del canal y evitando el cambio de orientación del pez. La forma rectangular del componente de canalización del prototipo actual fue diseñada para experimentar con peces de talla adulta, cuya dimensión resulta excesiva para experimentar con peces de talla alevín y juvenil. El rediseño de la forma del canal, tendría la ventaja de permitir el flujo de peces de las tallas alevín, juvenil y adulto.

Al cambiar la forma del componente de canalización, implicaría un ajuste del componente de iluminación del prototipo propuesto en esta tesis, si se desea mantener el contraste en las imágenes capturadas para la medición de la trucha arcoíris. De igual forma, se requiere ajustar la posición de la cámara de adquisición de imágenes digitales dentro del prototipo de medición.

También debe notarse, que investigar una nueva forma del canal del prototipo, evidentemente requiere analizar materiales alternos compatibles al componente de iluminación que permitan resaltar el cuerpo del pez dentro de las imágenes adquiridas.

Por otro lado, el prototipo de medición actual contiene dos posibles salidas para separar a los peces una vez estimada su longitud. Sin embargo, en esta versión del prototipo no se consideró un sistema de separación. Por lo tanto, se propone investigar una forma de separación automática de los peces usando compuertas una vez estimada su longitud, para decidir el estanque donde se depositará al pez.

Por otro lado, conforme a los tres problemas identificados de un sistema automático de clasificación de peces (ver Sección 1.2, Capítulo 4), se recomienda investigar un proceso automático para la separación e introducción individual de los peces, el cual se podría integrar al prototipo de medición propuesto en esta tesis para obtener un proceso de medición automatizado.