Sustainable Recreational Fishing Using a Novel Electrical Muscle Stimulation (EMS) Lure and Ensemble Network Algorithm to Maximize Catch and Release Survivability

PosAIdon: a high-tech lure for sustainable sports fishing

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ABSTRACT

With 200-700 million anglers in the world, sportfishing is nearly five times more common than commercial trawling. Worldwide, hundreds of thousands of jobs are linked to the sportfishing industry, which generates billions of dollars for water-side communities and fisheries conservatories alike. However, the sheer popularity of recreational fishing poses threats to aquatic biodiversity that are hard to regulate. For example, as much as 25% of overfished populations can be traced to anglers. This alarming statistic is explained by the average catch and release mortality rate of 43%, which primarily results from hook-related injuries and careless out-of-water handling. The provisional-patented design proposed in this paper addresses both these problems separately. First, a novel, electrical muscle stimulation based fishing lure is proposed as a harmless and low cost alternative to sharp hooks. Early prototypes show a constant electrical current of 90 mA applied through a 200g European perch’s jaw can support a reeling tension of 2N — safely within the necessary ranges. Second, a fisheye camera bob is designed to wirelessly relay underwater footage to a smartphone app, where an ensemble convolutional neural network automatically classifies the fish’s species, estimates its length, and cross references with local and state fishing regulations (ie. minimum size, maximum bag limit, and catch season). This capability reduces overfishing by helping anglers avoid accidentally violating guidelines and eliminates the need to reel the fish in and expose it to negligent handling. In conjunction, this cheap, lightweight, yet high-tech invention is a paradigm shift in preserving a world favorite pastime; while at the same time making recreational fishing more sustainable.
1. INTRODUCTION

With 33 million anglers in the United States alone, and an estimated 200-700 million worldwide, recreational fishing is the second most popular outdoor activity next to jogging. In the US, the sportfishing industry supports 828,000 jobs and contributes $115 billion to the GDP; so it is unsurprising that many lakeside communities rely on fishing tourism for their citizens' livelihoods. Not only are sportfishers a significant economic force, they are also champions of conservation — generating $1.45 billion for fisheries through license fees and equipment taxes in 2010 alone [1]. However, sportfishers also pose significant, difficult to regulate, and difficult to quantify threats to marine ecosystems. Though it may seem intuitive to conclude that any environmental risks lie with giant commercial trawlers, a closer look reveals that there are five times more sportfishers than commercial fishers. Collectively, they contribute substantially to overfishing and loss of biodiversity as a result of high catch and release mortality.

1.1 Catch and Release Mortality

On average, 43% of fish caught and released by recreational anglers die from related complications; the majority of them within 72 hours. Human ignorance is a driving factor behind this statistic, as improper handling of fish contributes a large portion of these deaths. However, humans cannot be entirely blamed as fish by nature are very vulnerable out of water. For example, holding a fish by the gills, vertically, or simply not supporting its weight correctly can cause fatal internal organ damage. Figure 1 illustrates two common mistakes. Furthermore, even if an experienced angler gently handles and quickly removes hooks from a fish, merely bringing it out of the water can lead to its death. Many fish species possess a swimming gall bladder that acts as a pressurized ballast tank. When pulled out of the water too quickly, this bladder can overinflate,
preventing the fish from re-submerging when released. Due to this phenomenon, keeping a fish out of water for a full minute before releasing increases average mortality to 72% [2].

![Fig 1. The position shown on the right is so common that anglers refer to it as the “death grip”](image)

**1.2 Overfishing Regulations**

A Science journal paper published in 2004 analyzing 22 years’ worth of fishing data shocked the scientific community by revealing that nearly 25% of overfished species can be traced to sportfishers [3]. Before then, and even now to a degree, individual catch and release anglers were assumed to have no measurable impact on the environment. But the high catch and fish mortality in conjunction with the enormous popularity of this hobby should have been enough evidence on its own. Since then, many states have strengthened guidelines, suggesting a minimum size, fish bag limits, and allowable fishing seasons to protect at-risk species. With so many regulations that often vary from lake to lake within the same state, people still make mistakes [4]. These mistakes multiplied by the millions of anglers in the world lead to the surprising results reported in the Science study. Figure 2 displays sample regulations for just saltwater fishing in the state of Maine.
In this paper, we propose a smart and sustainable fishing technology. Thus far, most tech solutions have been aimed at commercial fisheries and few basic designs in sportfishing, such as barbless hooks, have proven to only be marginally useful [5]. The next section introduces the electrical muscle stimulation lure as well as the deep learning workflow, including network architectures and relevant data augmentations. In section 3, an experimental setup for the lure is explained and a trained neural network model is demonstrated.

2. METHODS AND MATERIALS

The objective of this project is to invent a technology for recreational anglers that prevents overfishing through reducing catch and release mortality. Firstly, sharp and potentially lethal hooks are replaced with a non-lethal electrical muscle stimulation lure, significantly reducing the likelihood of injury to a fish’s critical organs. Second, a deep learning based computer vision and telemetry system inside a fishing bob detects the fish’s species and automatically determines whether it meets the numerous state regulations — all without removing it from the water.

2.1 Electrical Muscle Stimulation Lure

Electrical muscle stimulation (EMS) uses two electrodes to send current impulses through tissue, contracting targeted muscles by simulating the action potentials generated from the central nervous
system [6]. Currently, EMS is an FDA approved accessory to physical therapy, preventing muscle spasms and improving blood flow during exercise. It is important to note that an EMS fishing lure is unique in design and application from electrofishing, which is a surveying method that directs fish movement through galvanotaxis: the process by which biological cells can sense electric fields [7]. Electrofishing does not require a fishing hook, and is banned for recreational uses. The EMS lure features an anode and electrode on opposite sides that will pass non-lethal current through all major muscle groups of a fish’s mouth.

### 2.2 Data Augmentation

Before development of the deep-learning model, a robust and scenario-accurate dataset was required to ensure optimal performance in a variety of fishing conditions. This paper uses the *Open Images Dataset V6* developed by Google with a total of 125,436 images of over 600 different fish species [8]. However, given the recent advancements of transfer learning models with pre-initialized weights optimized for classification, it is unnecessary to utilize 100% of the data. A data pre-processing script was written to keep only images with distinct features, as characterized by the structural similarity metric and mean square distance:

\[
MSE(I, J) = \sum_{i=0}^{n-1} \sum_{k=0}^{m-1} [I(i, k) - J(i, k)]^2
\]

Essentially, this algorithm takes both the content of the image and its related similarity in shape, orientation, lighting, and intensities into account, ultimately decreasing the testing size by over 85%. Figure 3 illustrates the patchy by patch image comparison metric.
The second step of the data augmentation was to modifying the downsized image dataset to match camera hardware specifications and simulate specific scenarios and variables. Samples of each of these steps are displayed in figure 4. Firstly, a fisheye camera lens model was chosen for its wide field of perception. Thus, a fisheye transform was applied to a 2D image, mapping the extremes of the image to a spherical surface. It is also known that water acts as a light filter, causing images taken in deeper waters to be of lower contrast. To simulate these effects, randomized contrast enhancements are made to the training data. Additional scattering noise of variable intensity is applied to simulate water turbidity. Finally, due to the camera framerate, blurring artifacts will appear in the direction of a fish’s movement. This is achieved by a 1D convolution in the direction of the fish’s motion, where $h$ is the base image and $f$ is the blurring kernel:

$$ (h * f)(x) = \int_u h(x - u)f(u)du $$

![Original Image](image1.jpg) ![Motion Blur](image2.jpg) ![Image Noise](image3.jpg) ![Fisheye](image4.jpg)

Fig 4. Sample images of various image augmentations
2.3 Classification, Segmentation, and Network Architectures

Two primary goals and two secondary goals existed for this deep learning model. The first two goals being a network that can accurately identify the species and region in the image frame where a fish is located. This was achieved using a region-based convolutional neural network that was trained via transfer learning from the YOLO v3 model. Modifications were made to the algorithm so that the coordinates of the bounding box in the frame can be displayed and used to compute the size of the fish. However, one of the limitations of the R-CNN is that it lacks depth perception so size prediction will generally be inaccurate. In order to correct this, we implemented Google’s FCRN model for depth perception. Overlaying this information with the R-CNN allows for greater dimensional accuracy from the same image.

Fig 5. Images of the YOLO v3 Architecture
Presented above is the network architecture of the RCNN. A couple notable features about this model is that it segments object sizes within the image to speed up detection and segmentation. By training this model on hundreds of different species of fish, a comprehensive model was developed for live-time detection. Additionally, with some modifications, the pixel positions of each bounding box is stored in order to be used for size predictions of the fish to be fishing session. This allows for longitudinal data tracking while not consuming significant battery or memory on the recording device.

The depth perception network takes an input image and differentiates the visible layers. In doing so, this allows for the coordinates determined by the RCNN to be contextualized with depth, leading to a more accurate analysis of the shape and size of the fish being inspected. With future applications, this research allows for more detailed predictions about the fish’s characteristics such as weight.

Fig 6. Image of the FCRN Depth Perception Network
3. EXPERIMENTS AND RESULTS

The data and results obtained at the time of this paper demonstrate a successful system. Freshly caught fish purchased from the market show promising responses to the EMS fishing lure, and the electrical design has proven to be compact and lightweight. The classification system simultaneously achieved high performance accuracy and low computational expense.

3.1 EMS Fishing Lure

The fishing lure is based on the most effective pre-existing lure shapes, but excludes the use of traditional hooks. Instead of the hooks, two electrodes consisting of braided aluminum wire acting as electrodes were used. Metallic foil, such as aluminum foil was first considered but abandoned in favor of the wire because of durability reasons. The experimental setup for measuring the clamping force of the fish’ jaw consisted of the lure, EMS-unit for applying the high frequency AC-voltage, a force measuring winch for pulling the lure, and a laptop to record the pulling data.

As the control experiment, the EMS-unit was first turned off and the winch pulled the lure out of the fish’ jaw. The experiment was then repeated but the EMS-unit was switched on. For the 200g European perch, 2N of reeling tension was achieved at a set stimulation current of 90mA. This value demonstrates that the EMS lure is capable of catching small fish, but is also able of being scaled up. The resistance between the lures electrodes, when in the jaws of the fish, was measured.
to be 21.8kΩ, meaning the voltage needed for the current of 20mA through ohms’ law is 436V. These specifications are within feasible ranges of small-scale power sources and voltage boosters.

**3.2 Network Results and App UI**

The RCNN model was trained in Apple’s CoreML 3 and CreateML frameworks in order to streamline the application development process. Training took 7 hours to complete for the RCNN on a device without a GPU. After training the network, a series of real time tests were run on a mobile device to ensure its compatibility and viability as a truly mobile framework. After 3 hours of continuous data tracking, it was determined that the object detection model ran in real-time at 24 fps. In order to save power and decrease latency, the depth perception model is only activated when a fish is detected in the frame. At the end of the three hours of feed capture, the application used 15% of the battery translating to roughly 400mAh. This suggests that the application runs very efficiently with respect to its computationally heavy operations.
Fig 9. Images of the app software applied to real-world data

The UI was developed to be intuitive yet provide all appropriate information in the images you can see. The leftmost image, is the UI showing the Depth perception output of the FCRN of the given fish frame. In the middle, an image can be seen of a screen capture from the RCNN detecting images of fish in the water using the phone camera, additionally, the continuous frame rate is posted in the right hand corner. The rightmost screen is a visualization of the future UI implementation to allow users to easily see and adhere to fishing regulations in their region and get telemetry of their catches. Based on the species classification and state by state regulations, the app recommends to the user whether or not to remotely release the fish, avoiding the out of water handling that leads to high catch and release mortality.
3.3 Circuit Design and 3D CAD Models

Power supply and charging block uses TLP4056 Li-Ion charging IC to charge the 18650 cell and FS312F-G protection circuit along with its complementary MOSFETs for overcurrent, overcharge and over discharge protection. 3.7V from the battery is then fed into a SDB628 DC-DC step up converter IC, which boosts the voltage up to 5V to feed the ESP-EYE camera/machine vision module. A LM1117-3.3V is used to step down the input voltage to 3.3V in order to drive the ESP32 used for controlling the hook.

The ESP-EYE is a new age machine vision integrated camera and video streaming module designed around the ESP32 microcontroller. It is used here only for video streaming into a smartphone that does the video processing and fish detection but this could possibly be streamlined in the future to be done fully in the fishing bob. The actual control for activating/deactivating the EMS lure is done with an external ESP32, that listens either Wi-Fi or BT for turn on/off commands and will then drive the power MOSFET at around 1KHz frequency. This 1KHz power signal is fed into a transformer that steps the 5V up to required 492V. The transformer also has a fast standard fly back diode. The 492V is then fed through thin magnet wire (0.2mm D) alongside the fishing line to the EMS lure. The 492V won’t be harmful for humans nor the fish as the input
current drops down as soon as it strikes through the fish. The system code streams video from the ESP-EYE into the user’s smartphone. A machine learning algorithm detects when a specific type of fish bites into the hook and sends a turn on command to the ESP32. The ESP32 then drives 1KHz signal to a MOSFET, which drives a transformer that then feeds the lure and causes the fish’ jaw to lock down on the lure.

4. DISCUSSIONS AND CONCLUSIONS

The objective of this project was to develop a safer and more effective way of sport fishing. In order to do so, we took a two-pronged approach using a novel hardware and software implementation to accurately and safely identify fish. The hardware implementation was developed such that it didn’t involve hooks which can potentially harm the fish, rather used an electrical stimulation lure to close the fish’s mouth painlessly. To provide pertinent information about the fish and ensure that fishers are adhering to state regulations, an application was developed using deep learning, computer vision, and cloud interface. The software can accurately detect fish in a given frame from a video stream and also contextualize the image with depth perception. Future implementations will also include a weight prediction and state regulation guidance features as seen in our results section.

While we were able to develop a viable fishing rod Prototype, given current circumstances due to the global pandemic, going outside and getting viable field data was not possible currently. However, an extensive set of structural, electrical, and mechanical tests were run on the fishing rod to ensure its reliability and functionality. There are two tests we wanted to conduct to create a comprehensive analysis of our rods performance for different species and size of fish. The first being fish clamp strength vs current applied to the lure and the second being clamp strength vs fish
weight for a given current value. In the future, once we have access to recreational fishing sites available to us, we can conduct these tests and fine tune the rod even further for a more ethical and effective fishing experience.

The current deep learning implementation for fish detection and depth perception work on par with widely accepted academic standards with a validated accuracy at ~89%. Additionally, these networks run in real-time on a mobile device making it viable for all users without expensive hardware to run these computations. With the future implementation of geotracking, weight prediction, and statistics sharing, we can serve as a supplement to an already large online fishing community with apps like Fishbrain. The software allows fishers to easily integrate the new fishing rod and platform into their existing workflow with negligible drop in their experience.

Our team met at the Intel International Science and Engineering Fair. Nathan and Pete were already fellow researchers in machine learning and engineering, using their skills for environmental and medical impacts. Krithik met Nathan at the pin exchange where they discussed their respective projects. As the immediate applications and results became apparent, Krithik joined the team to address the computational aspects of computer vision analysis for safer sport fishing methods, in addition to the economic viability and planning. One of the biggest obstacles overcome by this team was to cohesively create a team during a pandemic that all live in different states / countries.
5. REFERENCES

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5.2 Image Citations

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Note: all other images are original, or originally generated