



Developing an Ornamental Fish Warehousing System Based on Big Video Data

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Abstract: We have developed an ornamental fish warehousing (OFWare) system based on big video data. The system is an application paradigm of information and communication technologies for traditional industries, specifically in the fields of aquaculture and agriculture. Live creatures are the main products of these industries, raising challenges for warehouse management. Warehousing of high unit-price ornamental fishes such as koi, stingray, and arowana is even more difficult since, in addition to counting and classification, such warehousing requires the identification of individual animals whose shapes and texture patterns vary as they grow. Therefore, rather than using invasive RFID-based systems, we combine mobile cloud computing and big data analytics techniques including image and video collection and transmission using handheld mobile devices, unsupervised texture pattern classification of fish tank videos, fish image retrieval, and statistical analysis. The proposed system is scalable based on a Hadoop framework and a small set of a single name-nodes and data-nodes can identify a particular fish among 500,000 koi in 7 seconds. The proposed warehousing system can form the basis for the development of breeding histories, anti-forgery certificate, and aquaculture business intelligence.

Keywords: aquaculture business intelligence; big video data; image retrieval; mobile cloud computing; machine learning; ornamental fish warehousing system

Introduction

The aquaculture industry in general, and the ornamental fish industry in particular, can benefit significantly from appropriate application of information and communication technologies. For example, the ornamental koi fish market is a billion-dollar global industry, producing quality fish requires years of careful breeding, making it difficult to grow businesses beyond a certain scale because of the challenges of warehouse staff accurately identifying individual koi in group pools. Even experienced staff can easily misidentify fish, potentially resulting in fish being sold for less than their true value. Traditional RFID-based systems require time

and labor costs to tag individual fish, a process which can be damaging or lethal to the fish. This paper proposes the use of an image retrieval-based system for the warehouse management of ornamental fishes. The proposed method uses smartphone video of a fish tank to automatically count and identify individual fish through unsupervised classification and by capturing multiple images of each individual fish. To enhance system performance, we offload image-processing tasks along the network path from the handheld client to a cloud server. The handheld device performs image resizing and human-aided segmentation. The RESTful operations [2] allow for image and data access between the mobile device and the cloud server. The webserver performs image pre-processing such as morphological operations to extract each fish's texture features. The



cloud server in a Hadoop ecosystem performs image retrieval to update inventory and breeding history. The OFWare serves as the development platform for the following items.

- Inbound, outbound, breeding position change, and logistics: These scenarios require inventory updates.
- Business analytics: Feed, medicine, feeding supplies, environment construction, family variety, pattern preferences global distribution, price distribution, customer and pattern preferences analysis, attention analysis, and customized reports as well as the relations among these items.
- Breeding technique tutorials: Breeding history includes texture patterns of individual fish in addition to family variety and environmental sensor data. This reduces the time needed to track fish heritage and improves fish health management.
- Certificates of ownership, origin, and competition: Anti-forgery is achieved using photos of individual fish taken by visitors in different places and at different times. The process of transportation is recorded in the platform's database as well as in the

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staffs' handheld devices.

By applying mobile cloud computing and big video data analytics to aquaculture information, the proposed OFWare system provides value-added services for aquaculture business intelligence.

System Framework

Figure 1 shows the proposed OFWare system framework. There four subsystems: the handheld device, image preprocessor, machine learning engines, and the Hadoop ecosystem. The messages labeled with sequence numbers between subsystems are highlighted in red. The subsystems are described as follows.

Handheld device

A handheld video camera is used to upload fish videos to the web-based user interface. The user records a manual fish count in a temporary fish tank for transportation or inventory purposes. Advanced settings such as machine learning and related parameter options are also available for advanced users. After the video is submitted, the OFWare system returns the recognition results and the user creates or updates a profile for an individual fish, updates inventory, reads visualized data, or invokes accounting process. Through the *node.js* library [3], the OFWare converts the fish video into image sequences and encodes the images for transmission to the cloud server.

Image Preprocessor

The OFWare can simultaneously process multiple fish. A temporary holding tank typically holds no more than 10 fish at a time, making it easy for a webserver to perform fish feature classification unsupervised. From the image sequence, the webserver segments each image into close-ups of individual fishes. It then extracts and collects the texture pattern features of each fish. To preserve the texture orientation, the feature extractor rotates and stretches individual close-ups to properly orient each fish image before extracting the features of the texture patterns. The features are based on LTP (local ternary patterns) [4]. Each fish's feature vector is a concatenation of LTP features of different color textures.

Unsupervised Feature Classifier

The unsupervised classifier classifies fish features in the image sequence. The OFWare then collects additional features for each fish in different conditions such as in different lighting, shadowing, and view angles. The unsupervised feature classifier generates more representative fish features for each fish. The user then



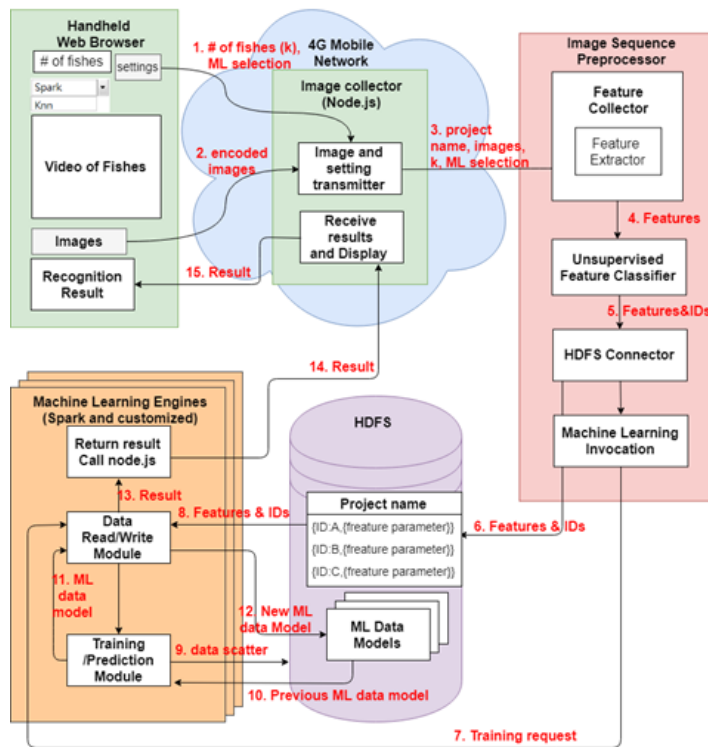
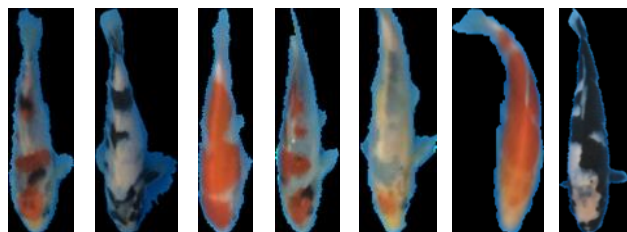


Figure 1. Framework of the proposed ornamental fish warehousing system.

sets number of fish in the temporary tank as the number of classes by the user in the web browser UI.



(a)



(b)

Figure 2. Image segmentation and warping to obtain each fishes' oriented close-up. (a): input image frame; (b): fish close-ups.

Hadoop Ecosystem

The Hadoop ecosystem serves as a distributed and

parallel computing environment for machine learning algorithms. Machine learning engines are accelerated

through a map-and-reduce mechanism and the Hadoop Distributed File System (HDFS) [5] stores large amounts of historical fish photos (an image database), texture patterns, pattern features, and environmental sensor data every time the OFWare is used. These data, along with feed and medication records, allow for the development of a fish breeding history. We use statistical analysis tools, such as Mahout [6], to infer the relation among texture patterns, feed, medication, and breeding environment. This allows for the development of expert knowledge systems which can be used to effectively train new staff in effective breeding techniques. The inclusion of pricing, customers, and GPS data allows for the development of business intelligence resources.

Machine Learning Engines

We built Spark machine learning modules [7] such as the support vector machine (SVM) [8], as well as customized machine learning modules such as the template matching in the Hadoop ecosystem. SVM predication allows for image retrieval by wrapping the newly extracted features as a database query. The OFWare updates the support vectors, which is the ML data model as illustrated in Fig. 1 by inclusion of the new features. Therefore, the OFWare records the latest features and representative close-up image each time a



staff member processes an inventory. This accounts for the time-variation of shapes and texture patterns as ornamental fishes grow. Moreover, in this way the OFWare detects newly purchased fishes not present in the OFWare database. Then OFWare asks the staff user to create new profiles (with automatically generated IDs in Figure 1) for the newly purchased fishes. Therefore, the OFWare is capable of incremental machine learning.

In Summary, we explain the red text message flow in Fig. 1 as follows:

- 1: The user provides settings including number of fishes in the temporary tank and selects the machine learning algorithm for training and recognition.
- 2: The image sequence is encoded in Base64 format for transmission across the Internet.
- 3: The images and system settings are sent to the web browser for image preprocessing including feature extraction and unsupervised feature classification.
- 4 and 5: The fish features are extracted. Appending auto-generated IDs, the OFWare invokes the machine learning engines on the Hadoop framework.
- 6: The new features are used to query the images in the HDFS.
- 7 and 8: Since fish textures may change as the fish grow, the new features becomes new training samples.
- 9-12: During training, the images and features are scattered for storage in the HDFS (message 9). Prediction uses the old machine learning model (message 10). The new features are used as the new training samples to produce the machine learning model (message 11) and update the model (message 12).
- 13-15: Finally, the OFWare sends the image query results back to the mobile device also using node.js for rendering on the web browser.

System Operation and Results

We illustrate two input cases of the operation. The first case has a still input image of multiple koi fishes and the second one uses a video of another fish tank. The still images can be used to check fishes' profiles while the videos depict the fishes' dynamic postures.

Still Image Input

Figure 3 shows snapshots of the OFWare used to process an inventory. Figure 3(a) shows the input image of a temporary tank with eight fish. The OFWare allows human-assisted marking (the light-blue line) to separate overlapping fishes. Figure 3(b) shows the database retrieval result of each fish. If a matching fish is found in the database, its image is shown in the upper row, otherwise a question mark appears in the upper row. A query failure indicates either that the query fish is a new acquisition or that the close-up image does not provide a clear texture pattern for the fish. Clicking on a question

mark or a fish image allows the user to browse the database for fish images similar to the query image and then select one from inventory. Clicking on one of the database images when browsing, the OFWare displays the profile details of the fish as in Fig. 3(c).

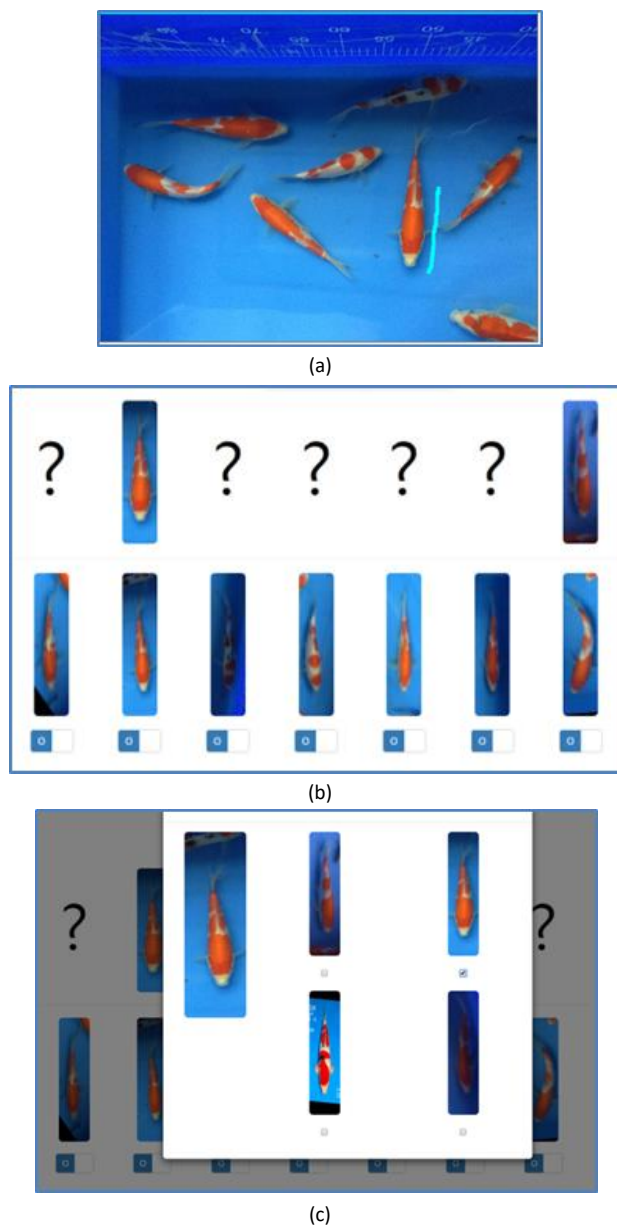


Figure 3. System operation snapshot: (a) temporary fish tank with eight fishes (seven are complete), (b) image retrieval result where two of the seven are found in the database (upper row: database images; lower row: query images), (c) most similar images for manual check.

Video Input

When a camera is set up above a fish tank for monitoring, the OFWare can perform an automatic inventory (see Fig. 1). Figures 4 (a)-(d) clearly show occlusion, blurring, and glitter in the video. The OFWare compensates for this interference by unsupervised

classification and machine learning since a video provides more information for each fish than a single image. Figures 4 (e)-(g) show the subsequent retrieval results. The left-hand images are older images, while those on the right are more recent (i.e., representative query images). A demonstration movie is available at <https://youtu.be/q4O5nGCAZ9w>.

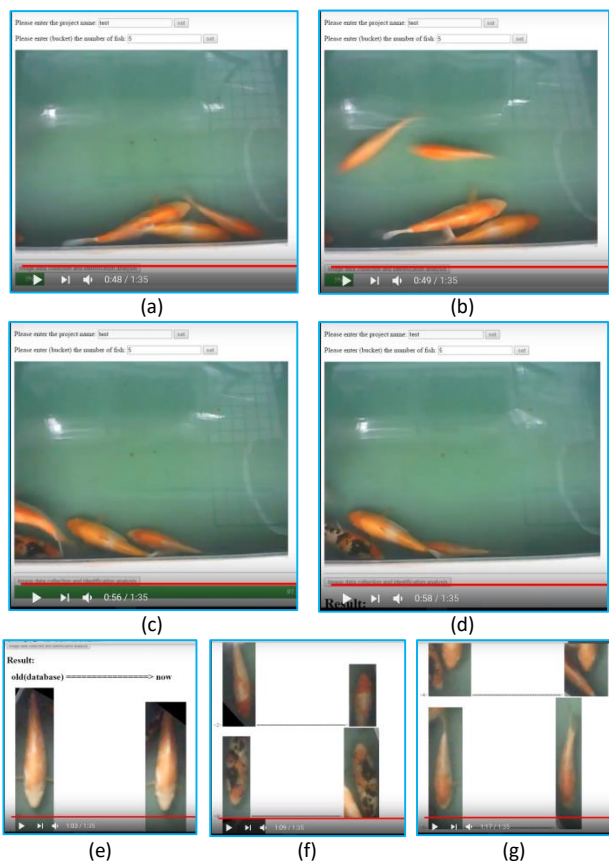


Figure 4. System operation snapshots using a video as input for the OFWare: (a)-(d) video clips, (e)-(g) subsequent image retrieval results.

Conclusion

This paper proposes an Ornamental Fish Warehousing (OFWare) system to provide business intelligence, breeding technique heritage and tutorials, certificates of ownership, origin, competition, and related anti-forgery mechanisms based on the integration of information and communication technologies including big video data and mobile cloud

computing. The platform is flexible such that customized and commercialized machine learning engines can be easily integrated into the system. The use of the Hadoop framework assures scalability. System operation examples show convenience and feasibility and achieve automatic warehousing using video input.

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