

Parallel Massive Dataset Cleaning

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Abstract

This project applies the decision algorithm[1] developed by Matt Pugh in 2015 on a massive parallel scale, to remove the large amount of False Positive fish detections in the Fish4Knowledge (F4K) dataset[2], without losing too many True Positives.

Also, according to Qiqi Yu's assessed runtime[3], the cleaning process will take more than 1000 days to complete on a 40-core machine. Simply putting the process onto parallel scale will not be sufficient, optimization of the code is also essential for making the processing more feasible.

This document describes the detail of various approach to reduce unnecessary work during pre-processing, improve the cleaning algorithm, and evaluating efficiency of different implementations of the machine learning techniques used. A more detailed roadmap this project is provided in the Chapter 1.

Acknowledgements

I would like to thank my project supervisor, Prof. Fisher, for his constant, patient support throughout the year. Without his expert knowledge in the field, it would be impossible for me to navigate through all of the data source and prior work of the Fish4Knowledge project.

I would also like to thank Mr. Matthew Pugh for finding out time answering my questions on the project, and precious advices on the implementation of his algorithms.

I must also extend gratitude to my friends, and my family back in China, for all their help and encouragement during my study.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(Jianmeng Yu)

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Chapter 1

Introduction

This project applies the previous work of Matthew Pugh[1] and Qiqi Yu[3] on massive parallel scale (detail in Chapter 2), while trying to reduce the computational cost of the cleaning algorithm. The main goal of this project is to produce a cleaned subset of a 1.6 TB dataset for future researchers.

1.1 Document Structure

Chapter 2 discussed some concept, designs used and the previous work of the project.

Chapter 3 described the details of the data sources, storage and preprocessing used in the cleaning algorithm.

Chapter 4 describes the first stages of the cleaning: early detection removal, feature extraction, preprocessing for classification in the next stage.

Chapter 5 discusses the final classifiers used in the cleaning, with evaluation of the results and comparison between different algorithms.

Chapter 6 contains the conclusions and possible future work needed for the project.

1.2 Fish4Knowledge Data Set

The Fish4Knowledge (F4K) project, funded by EU's Seventh Framework Programme (FP7), studies environmental effects by analysing raw videos and extract information

about observed fishes from it, so researchers could use it for studies without much programming skills.

The project acquired video data collected by Taiwan Ocean Research Institute, they set up 9 cameras in different coral reef areas such as Nanwan National Park (NPP), Lanyu, and Houbi Lake (HoBiHu) in Taiwan. After 5 years of filming, the project recorded about 524,000 10-minute video clips, with a total size of 91 TB, and approximately 1.4 billion fish detection were found in the videos, we call this the F4K Original Data Set (FDS).

In attempt to reduce the dataset, F4K project developed and applied a species recognition algorithm, which extracts all detections as 100x100 RGB images and it's description files, reducing to approximately 839 million detections. These summary files have a combined size of 1.6 TB, this is called Reduced FDS (RDS), more detailed composition of these are described in Chapter 3.

The above reduction get rids of some of the False Positives (object that are not fish, recognized as fish) from FDS, unfortunately, there are still a lot of False Positives, a classification schema is created to identify the detections.

1.3 Classification Schema

According to previous work of Matthew, 10 different classes were used to mark the training dataset, and later used in different classifiers for fitting. Fig 1.1 shows manually picked example from each of these classes.

The classes can be divided into 3 main categories:

I Not A Fish - These detection are marked for removal in future.

- 1 Compression Artefact - During the process of recording video, some bits were dropped during transmission of the compressed video. These detection usually have a rigid square shape.
- 2 Illumination Artefact - Lighting changes recognized as fishes, some are caused by refraction of turbid water, some are caused by light reflecting planktons.

- 3 Background Vegetation - Some of the video are captured with dynamic background, where the swaying plants are recognized as fishes.
- 4 Others - Everything else, this includes large floating matters, empty contours created by previous algorithms.
- 5 Unknown - Because of reasons like lighting and stretched video frames, it's uncertain the detection is fish or not.

II A Fish - These frames are useful for future researchers.

- 6 Good Boundary - With clear ocean as background, these fishes have good boundaries, and is useful for future species recognition.
- 7 Partial Fish - Mostly good detection boundary, but part of the fish is cut-off for various reasons.
 - i Fishes cut by frame boundaries.
 - ii Fishes are covered by vegetation or other fishes.
 - iii The fish is too big for the 100x100 boundary.
- 8 Bad Boundary - The fish is clearly captured, but the boundary extracted is useless for research.

III A Fish, but not useful - These frames detects fishes correctly, but misleading information may be extracted, it's unsure these frames should be kept or not.

- 9 Other Errors - like compression artefact are found in the image.
- 10 Multiple Fish with shared contour.

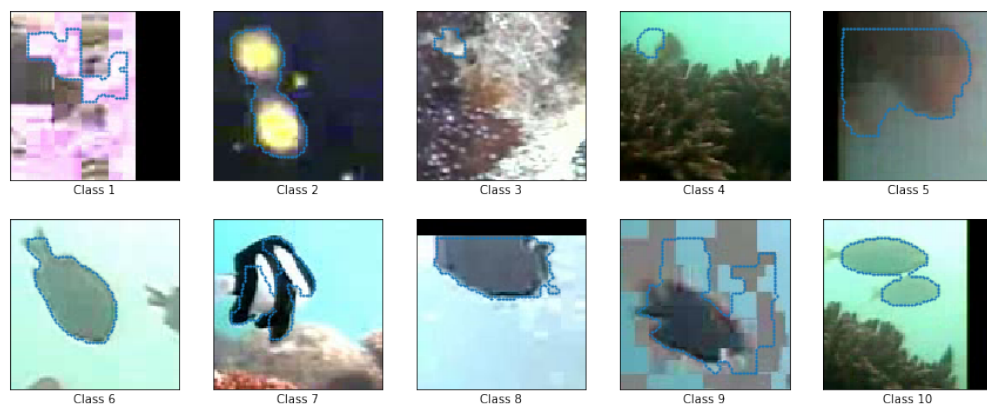


Figure 1.1: Example Detection From Each Class

1.4 Pipeline Classifier

The main part of the project is to translate and apply the pipeline classifier, designed by Matthew. However under limitations, the pipeline itself could not be applied directly on parallel scale.

The first limitation is the SQL database, which stores the track and contour information of the image. However the SQL is too large and slow for the project, To make the extraction more sensible, a Python script were used to partition the SQL. This potentially cuts the runtime to about 10% of the original design, and removed the need of a server. More details of this modification is in Section 3.2.

To further reduce the cost of cleaning, and attempt of translating the pipeline into Python was used, however the effect isn't significant, more details are in background Section 2.2.

Before sending the data into the classifiers, preprocessing is needed to give a more sensible result, which is the slowest part of the pipeline after removing SQL server. In Matt's thesis, a Frame Edge Indicator Function (FEIF) is used to directly reduce the amount of frames need to classify, after improvements and new addition in Chapter 4, cleans out about 20% of the detection.

After extracting and reducing features, they are fed into 3 Convolutional Neural Networks (CNNs) and 10 Support Vector Machines (SVMs), then applying them a top N algorithm is used to produce final result. This part is mostly trivial since the classifiers are already trained by Matt. Some further evaluation about other potential classifiers are in Chapter 5.

Figure 1.2 below is a diagram of the work flow of the pipeline classifier:

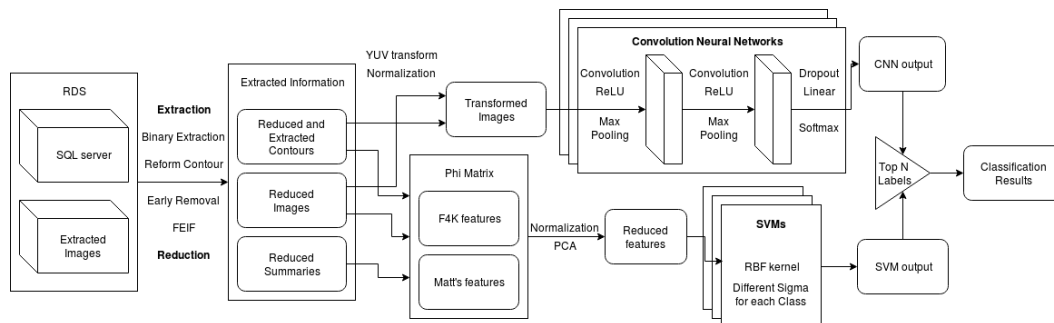


Figure 1.2: Pipeline Classifier designed by Matthew, modified

Chapter 2

Background

2.1 Big Data

Big data is one of the most hot trending topics recently, where the amount of the data generated is not possible to be manually analysed. Different to the popular text stream analysing, the project is more focused on image processing of a large collection. There are already some image processing library with work distribution framework, for example: Hadoop Image Processing Interface[4], Apache Spark based 4Quant[5], and other tool kits for parallelization.

Due to the limit of the scale, the project could not use a dedicated server for the cleaning, the Distributed Informatics Computing Environment (DICE) with Scientific Linux 7 (SL7) are used instead. The DICE machines are provided by The University of Edinburgh, in this project, approximately 200-300 student lab DICE were used. Also, a 256 GB disk space quota on Andrew File System (AFS) was applied for this project.

2.2 Translation from MATLAB to Python

Initially the project aims to translate the entire pipeline into Python, however when it comes to the feature extraction part, translating the code seems to become an unreasonable solution. The F4K feature extraction code developed by Huang have about 5,000 lines of code in MATLAB.

Usually most of the MATLAB code have equivalent library function from SciKit-

Learn/Scipy, however most of Huang's work consist of customized part that could not be directly translated to Python.

For example, the Gabor Filter used by both Huang and Matthew, are written by Ahmad Poursaberi from Tehran University, a different implementation (where scale of the filter is rotated, while their variance isn't) is used. This essentially requiring the project to re-engineer the whole F4K feature library.

Full translation could take a few weeks for the F4K feature, also because of the cleaning algorithm only need to run once, expected increase in performance need to be calculated to figure out which approach is faster. After time recording on various part of the algorithm, it's identified one of the slowest operation is 2D convolution.

Figure 2.1 below are test result of different 2D convolve algorithm. Where 2000 random 100x100 array is generated to simulate images used, and 5 random 5x5 filter is used, simulating both Gabor Filter and CNN used in the pipeline. By enforcing the maximum computational thread to 1, the result shows that 2 algorithm in Python is faster than MATLAB.

- TensorFlow's conv2d, while faster than all other library, it has a significantly high memory usage due to the tensor data type, potentially causing thrashing on machines.
- Scipy.NDImage's convolve, giving almost same performance as MATLAB.

After above analysis, it's clear that re-engineering the MATLAB code is likely to spend more time, so a library called PyMatlab will be used to compute the F4K features in a MATLAB session instead, while other unfinished part of the pipeline will be translated to Python.

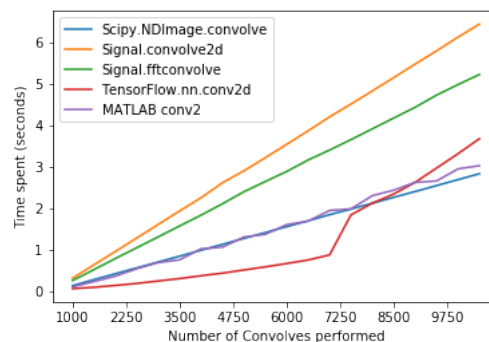


Figure 2.1: Test runtime of different 2D convolve algorithms.

2.3 Message Passing Interface for Python (MPI4PY)

Since the project uses student lab DICE machine as processor nodes, the task distribution system need be scalable, as the machines available may fluctuate. A short bash script combining ping and ssh is used to update the \$HOSTS to a up-to-date list of available DICE machines.

Mpi-master-slave, a small python library with MPI4PY is used to distribute all the job among the available machines. For example, if there is 4 machines available, with the following command:

```
>> HOSTS=basso,battaglin,belloni,bergamaschi
>> mpiexec -n 4 -host $HOSTS \
.. python ~/f4k/runMulticoreFeatureExtract.py
```

The python program will be started on above 4 machines, with the first one (basso) being the "master", distributing task to "slaves", which is every other node in \$HOSTS.

While "slave" node doesn't receive a EXIT signal, it will keep sending master READY signal, and after receiving work data from "master", it sends a DONE signal back to "master", and then goes back to the READY loop. The "master" creates a work queue of all the videos need to be processed, and send it to "slave" with START whenever it receives READY, it keeps sending the work until the work queue is empty, when every work is marked as finished, it broadcasts EXIT signal.

For all the "slave" node, Python's MultiProcessing and MATLAB's ParPool is used to fully utilize every core's computational power.

```

Mate Terminal
File Edit View Search Terminal Help

Progress: 8025/ 24101, took 1:42:53.243309. Slave: cagliari started 24d3c588b76e017946384e8b517ecc30#201108061220 with 2078 frames
Progress: 8026/ 24101, took 1:43:05.574027. Slave: cesena completed 2d16c39a9eaf071b9e92eb1f0147760#201105270600 with 2083 frames in 0:05:05.013049
Progress: 8027/ 24101, took 1:43:12.217072. Slave: hazlerigg completed 2f111ca4f3f408949b3d4f5c17ebcb1#201209150010 with 2070 frames
Progress: 8028/ 24101, took 1:43:32.188628. Slave: tortona started 27744d972b3f4bde4451b1038658ab0#201005150000 with 2095 frames in 0:06:37.944651
Progress: 8029/ 24101, took 1:43:32.606795. Slave: cremona started 244bc2b5e7cea801d984fceb47c51a7#201106131500 with 2077 frames
Progress: 8030/ 24101, took 1:43:46.276203. Slave: maryport completed 2a43db18770d0245d89c40e2c28695ca#201106240850 with 2081 frames in 0:04:13.012421
Progress: 8031/ 24101, took 1:43:59.191510. Slave: catania completed 2a6d8162a8ecf22af537cabaa5a028f#201203081240 with 2077 frames
Progress: 8032/ 24101, took 1:44:03.564759. Slave: teramo completed 27c995bae5fadf6a5f3858c55a0d91#201209231400 with 2084 frames in 0:06:09.057827
Progress: 8033/ 24101, took 1:44:22.550770. Slave: seaton started 2cb862fbaa6e15376b1d118985c77e#201205001640 with 2077 frames
Progress: 8034/ 24101, took 1:44:38.621003. Slave: ingleton completed 27ea0bcae8960567bd71b453668b335a#201303231030 with 2081 frames in 0:05:51.965011
Progress: 8035/ 24101, took 1:44:44.156501. Slave: barrow completed 28cbf0b3fa54669b1c2d219070af80b#201204191720 with 2077 frames
Progress: 8036/ 24101, took 1:44:49.608336. Slave: thropton completed 276df21f537ea4d4fc1e879bee1ef683#201003071540 with 2082 frames in 0:06:07.037897
Slave: thropton started 207e8c79199425ca59d9716201037c61#201102140910 with 2077 frames
Slave: thropton completed 219d6a0dc1ada625b6dcd4750fad7085#201211281610 with 2084 frames in 0:07:39.882613
Slave: thropton started 2f66b84c22d68810210986d2bfb6bb#201212121620 with 2076 frames
Slave: thropton completed 2e254cf4744a2b0fce19908f55416e89#201204201430 with 2085 frames in 0:08:02.966100
Slave: thropton started 238132acc86f1b1a6806ad4f8d12d8fe#201103241450 with 2076 frames
Slave: thropton completed 22f923fec9e6c013d7c64eb04275e0e1#201011191600 with 2079 frames in 0:04:04.852847
Slave: thropton started 2fa0c60279460e99d829b9575cal250#201207111710 with 2076 frames
Slave: thropton completed 204b4dca173e12a372454d1ca677eae#201107200620 with 2083 frames in 0:07:02.079017
Slave: thropton started 238cb7a1ab3c53b8a447becf1cfd1fc#201209011140 with 2076 frames

```

Figure 2.2: Running the MPI program on MATE terminal

2.4 CPU Hogging and Memory Thrashing Prevention

The project take place on public student lab provided by The University of Edinburgh, it is important that the cleaning algorithm is only running in the background, and not affecting other user's work.

For the CPU usage, SL7 provides a `NICE` command, allowing the program to have a higher `NI` value which gives lower priority on CPU scheduling. After testing it on the machines, it is reported that the code cause the lab to heat up, and some machines are starting to become unresponsive after running code on it.

The process is further tested on an empty lab with 20 machines, after running the extraction overnight, the lab is only slightly warmer than other labs. This problem could be solved simply by ventilation system installed in the lab.

Another problem is more problematic, loading a video with 10,000 frames and all my library function will took about 3 GB space in physical memory. After unreferencing every variable and force the garbage collecting mechanism, it still leaves 10% of the memory in use, this eventually piles up and thrash the memory. A solution is to spawn a sub-process and kill it after it's finished, but this increases the time to reload the python libraries, taking about 5 to 60 seconds per video.

2.5 Error Recovery and Progress Record

The project is running on massive scale, error handling plays a more and more important role in the processing. When an error is caught when processing a video, it immediately sends "master" a `DONE` signal, but with a failure message. The "master" will remove that "slave" node and put the job it fails and put it back to the start of the work queue, allowing it to be re-scheduled again.

In case of master crashes and other situations that MPI process is killed, all of the nodes will stop and some progress recording mechanism is needed for resuming progress. After all the output is stored on the disk, another empty file with `.complete` suffix is created. So the "slave" process could know if a video is finished processing, or killed before it finishes storage. With this file existence check, repeat work after restart is greatly reduced, hence keeping the progress.

Chapter 3

Data Source

After the species recognition of the F4K project, three types of output file is stored:

- Extracted 100x100 RGB images, compiled into `.avi` video file.
- Corresponding summary of the video, recording detection id and bounding box sizes. Stored in comma separated values format, as `.txt` file.
- A `.sql` dump file of 500GB, from the database used for species extraction.

3.1 Extracted Images

During the species recognition, the bounding box and contour of each detection is computed. The bounding box consists of 4 values x, y, w, h , where x and y are the coordinate of the top left corner, w and h are the width and height of the bounding box.

For each video a `video_id` is generated, it consists of a 32 byte hash of video, a #, and the filming date of `YYYYMMDDhhmm` format. For every detection with w and h both smaller than 90, a process illustrated in Figure 3.1 is applied, where a 100x100 area is selected with top left corner coordinate $w-10$ and $h-10$ and cropped from the image. If the selected area is out of the range of the frame, those area will be filled with black pixels. Those cropped images are then stored in file `summary_(video_id).avi`, with detection id and w and h stored in corresponding `frame_info_(video_id).txt`.

There are a total of 396,901 of such videos, consist of 839,465,846 frames, sums up to a total size of 1.14 TB.

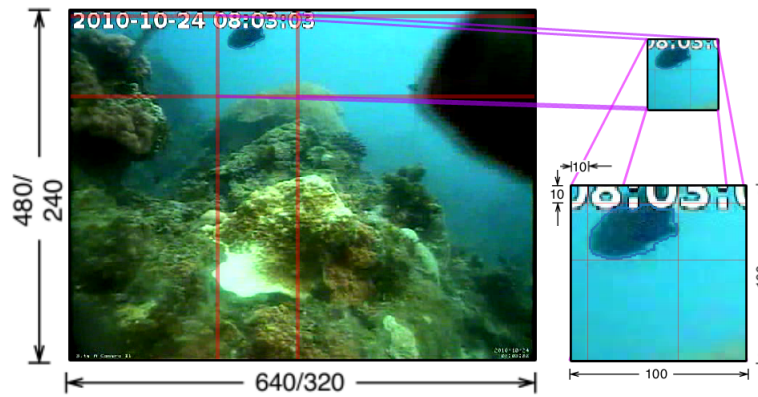


Figure 3.1: Process of Extracting Image

3.2 SQL dump file

The .sql dump file comes from the SQL workflow of the F4K project, which means not only details of fish detection is stored, other components irrelevant to this project is also stored.

Below is the schema of the "Fish Detection" table, this table takes about 326 GB, and is the only table that are actually needed in the cleaning.

```
CREATE TABLE IF NOT EXISTS f4k_db . fish_detection (
  detection_id INT(11) NOT NULL AUTO_INCREMENT,
  fish_id INT(11) NOT NULL,
  video_id CHAR(45) CHARACTER SET utf8 NOT NULL DEFAULT ,
  frame_id MEDIUMINT(9) NOT NULL DEFAULT 0 ,
  timestamp TIMESTAMP NOT NULL DEFAULT CURRENT_TIMESTAMP ON UPDATE CURRENT_TIMESTAMP,
  bb_cc BLOB NOT NULL,
  detection_certainty FLOAT NULL DEFAULT NULL,
  tracking_certainty FLOAT NULL DEFAULT NULL,
  component_id SMALLINT(6) NOT NULL,
  processed_videos_id INT(11) NOT NULL
```

There are other tables such as "Camera.Info" that shows the camera used for each video, with relatively small disk usage.

This .sql dump file is stored as plain text file that could be parsed into SQL code that loads the stored data. Under limitations of disk space and access speed, loading a large SQL database dump file into server and performing 400,000 queries is very unnecessary and time consuming, hence making it the slowest part of the cleaning. Also, the provided AFS quota could not hold all the information, an alternative is to use python script with standard stream pipeline to parse and partition the dump file into directly usable files.

3.2.1 Standard Stream based Extraction Script

Since each record needed for the cleaning are independent (given they have different video_id). If each detection are stored into a corresponding file with it's video_id, the information extraction will be much faster without the need to seek through all the records of other videos.

Because each detection is only need once during the extraction, and the dump file is too large for the RAM, standard stream pipeline a more reasonable choice for the parsing.

With simple Python functions such as `split()`, the record in the dump file of form:

```
INSERT INTO `fish_detection` VALUES (1) , (2) , (3) , (4) ... (N)
```

are parsed into directly usable list of values, separated by `newline` character.

This process makes the time cost for loading the dataset reduced to almost negligible amount. In Qiqi's estimate, the loading and preprocessing would took 800,000 hours (25,000 hours on a 32 core machine) in original design (double the time if considering her calculation error). After the extraction it only took about 0.3 second on average for a frame to be load and processed on a single computational thread. Which is about 70,000 hours, essentially cutting down the time used to 10% of the original.

3.2.2 Translation of Binary Data

With the above extraction, another problem arises, in the schema mentioned in section 3.2, there is a column called `bb_cc`, which means "Bounding Box Chain Code". This contains the `x, y, w, h` in original videos, and a chain code to store the data in a more compact format.

Also, since the binary file is stored as text file, a different encoding is used so it won't cause parsing fault during loading, for example, 8 consecutive 0 bits, the null character, are stored as two bytes in ascii format of `\0`. A cleaning function is used to enumerate through the raw bit array to translate them back to original values.

After comparing binary values of `bb_cc` and the corresponding detection image, it is found that the binary data is in the following format:

- First 42 (11,11,10,10) bits - `x, y, w, h` of the bounding box.

- Next 11 bits - X coordinate of the first contour point.
- Following 3 bits - Padding of zeros added to make length a multiple of 8.
- All other bits - Chain Code of the contour, 3 bits each. Pointing towards next contour point from previous one.

This process allows quick extraction of the contour, loading the image, summaries, and the contour information of a 1000 frame video into memory from AFS only took 1 second now, and removes the need to maintain a running SQL server.

3.3 Ground Truthing Dataset

In order to train and evaluate the classifiers, Matt and Qiqi manually marked a set of detections with the schema above. They chose a subset of the RDS, which is all the videos having id start with "13b". This subset of the RDS consists of 97 video files, and 154,042 detections.

However the marking was not able to cover all of the detection because of it's size. Moreover, some set of the detection is marked wrong because of the ambiguity of the classification schema. For example, a lot of the planktons are marked as fishes, and since class 9 (good detection with problem) is very rare, it's sometimes mistaken as class 5 (Unknown) or 7 (bad boundary). Some of the error patterns are not included in this video set.

Some special videos this ground truthing dataset doesn't contain was included, for example, video with high transmission error rate at Lanyu Site, videos filmed at stormy times (blurry camera) at HoBiHu site, and a video full of illumination artefact at camera 4 of NPP-3 site.

Chapter 4

Preprocessing

While the data source problem is solved, the most costly part of the pipeline will be the feature extraction for the SVM part. It's not sensible to send all of the RGB values of a image as direct input for the SVM, hence feature extraction and dimensionality reduction is needed.

To achieve the goal of removing False Positives without losing too many True Positives, some reduction method on the dataset is used before extraction of the feature, Early Video Removal was introduced and improved version of Frame Edge Indicator Function developed by Matthew was used.

4.1 Early Video Removal

During the feature extraction tests, it is discovered that loading a 40,000 frame video and extract features from it would take about 8 GB of memory space, if such video is processed on a node with RAM less than 8 GB, it will cause serious thrashing, rendering the node unresponsive. For machines having a RAM higher than 8 GB, it will still causes some disruption during loading.

While risking the chance of thrashing, these video took longer time to process, and most importantly, they are usually filled with False Positive detections. As discussed in Chapter 3.1, if a camera recorded 30,000 detection in 10 minute, means that in every frame of the original video, an average of 10 detection is extracted. By looking into these "outlier" videos, some patterns were found:

- Both Camera at Lanyu site are night-vision cameras, when they film during the night, a lot of light reflecting planktons close to the camera are recognised as fishes. Videos filmed during night have an average of 6974 detections. A 5% of the total detection comes from such videos, with the high False Positive rate, these videos can be safely excluded from cleaning.
- Videos full of compression/transmission errors, mostly happens at NPP-3 site camera 2 during June 2012 to August 2012. The camera seems to be falling down and change angles every few days. Even if there are no such errors, most of the detections are from moving background vegetation.
- One outlier video with 200,000 detection, consists of lots of repeating frames, possibly caused by bugs in previous extraction processes.

There are also some good video with high detections:

- Videos from NPP-3 site camera 3, at January 2010. These videos are captured at a higher frame rate, resulting in more detections. They usually contains lots of good detections.
- Dynamic background - Videos filled with moving vegetation, or refraction of sunlight. They usually contains lots of good detections.

Using the above patterns, if we remove all the videos recorded in the night, videos with 40,000 or more frames, and video recorded with above characteristics and 20,000 or more frames. About 8% of the detections can be rejected without need to extract them, saving approximately 200 days of computational time. Samples of rejected videos are in Appendix A.

4.2 Frame Edge Indicator Function (FEIF)

In Matthew's thesis, FEIF is used to identify if a fish is being partially cut by the frame. In FEIF, a boundary of video is defined, and if the number of the contour points outside of the boundary exceeds 25, the detection is then rejected.

However this function could not achieve the intention on some cases, for example, some videos have a darker frame edge, so even if a fish is cut by boundary, the contour points will be inside the boundary. Also, a large fish slightly touching the boundary will

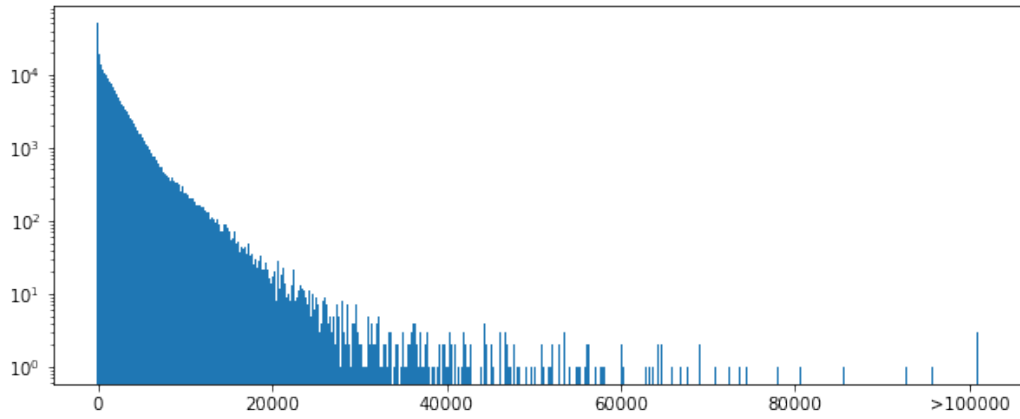


Figure 4.1: Log Scale Histogram of Detection Length

be rejected because the 25 limit, and small fishes may bypass the heuristics because of the size.

Following modification is added to solve the problem, by shrinking the boundary by 2 pixel, then increasing the limit of 25 to 40, and added new restriction: reject all the points with 25% of the points touching the boundary. About 15% of the dataset is rejected by it, saving about 400 days of computational time.

4.3 Feature Extraction

During the species recognition of the F4K project, 2626 features were used for computing detection certainty, on that basis, Matt added 29 new features focused on the edges of the contour. Then dimensionality reduction is applied to the features to reduce dimension of 2655 to 28.

This process takes about 0.3 seconds for each frame, cutting down the components shows the following result, sorted by time cost:

- Co-occurrence Matrix - these 720 features took about 0.2 seconds to compute.
- Affine Moment Invariants - these 105 features took 0.05 seconds to compute.
- Gabor Filter - these 160 features took about 0.04 seconds to compute.
- Rest of the features took almost negligible amount of time to finish.

Unfortunately after checking the features with PCA, these feature all took significant

part in the first 50 PCA components, removing any one of the 3 time costly feature will have a high impact on the result.

4.3.1 Matthew's Feature

This part of the generated feature consist of 4 parts: Animation Score, Boundary Curvature, Erraticity, and Gabor Filter on edge. This part of the pipeline is translated into Python as the original feature generation script is incomplete. Some inefficient for loops where translated using Numpy library to speed it up.

Animation Score is calculated for one whole track, where 5 frames are pick from the track, and squared sum of the change in pixels is calculated. This part isn't very useful because of the dynamic background of the image.

4.3.2 F4K Feature

4.3.3 PCA Analysis

4.4 Image Processing For CNN

In Matt's pipeline classifier, 3 different CNN were used on different type of preprocessed images. In CNN_N, normal image is used, in CNN_WC and CNN_BC, a masked image is used, filling the pixels outside the contour with white and black respectively. For all 3 type of images, and transformation to YUV color space is used, then the Y channel is normalized with mean and variance of ground truth dataset. A final color space of Y'UV is used for the CNNs.

Different to SVM feature, preprocessing for CNN took almost no time using OpenCV's image transformation.



Figure 4.2: Images on different stage of pre-process

Chapter 5

Classification

- 5.1 Support Vector Machines (SVM)**
- 5.2 Convolutional Neural Networks (CNN)**
- 5.3 Evaluation**
- 5.4 Potential Candidate of classifiers**

Chapter 6

Conclusion

6.1 Results

6.2 Future Work

6.3 Final Words

Bibliography

- [1] Matthew Pugh. Removing false detections from a large fish image data-set. Msc dissertation, The University of Edinburgh, 2015.
- [2] Fish4knowledge homepage. <http://fish4knowledge.eu/>. Accessed: 2018-01-08.
- [3] Qiqi Yu. Adding temporal constraints to a large data cleaning problem. Msc dissertation, The University of Edinburgh, 2016.
- [4] Introduction to hadoop image processing interface (hipi). <http://hipi.cs.virginia.edu/>. Accessed: 2018-01-15.
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Appendix A

Sample of Lengthy Videos

The videos below are some sample frames.

Words

Paragraphs



Figure A.1: Sample frames from a video filmed at night.



Figure A.2: Sample frames from a corrupted video.

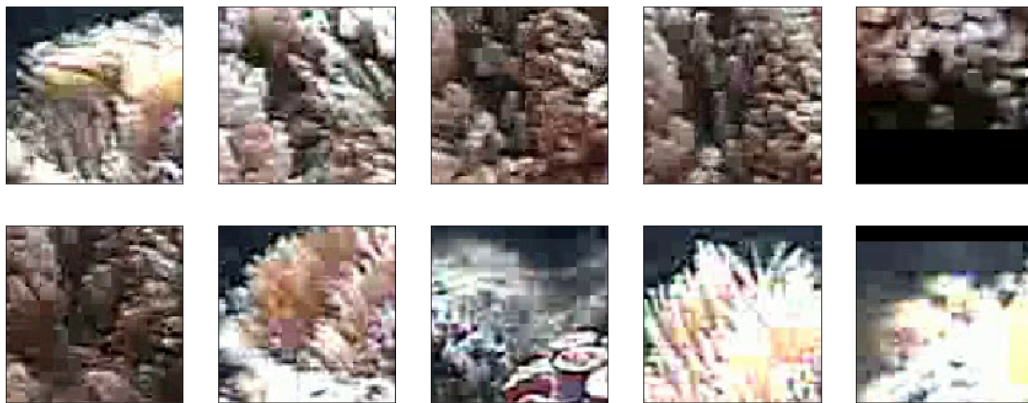


Figure A.3: Sample frames from a video with dynamic background.

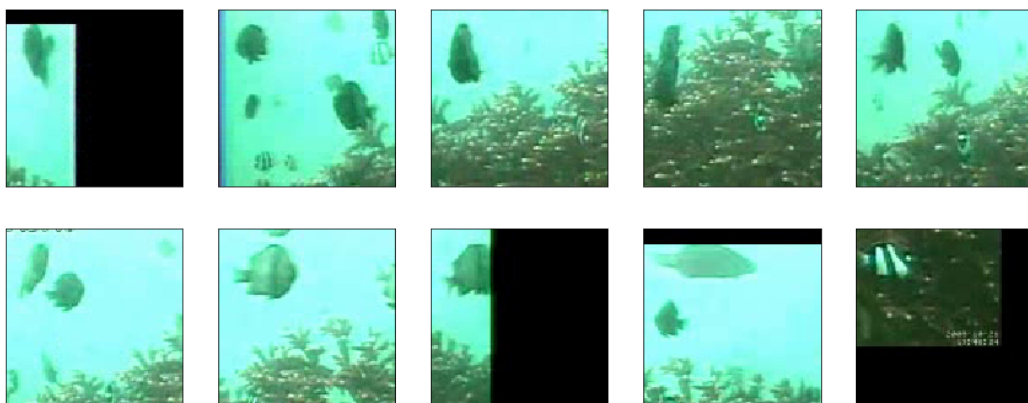


Figure A.4: Sample frames from a video with abnormal amount of fish.