Finding Dory Project Report

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July 3, 2022

Abstract

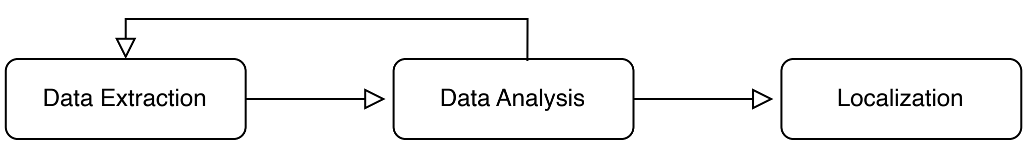
Brief summary of the proposed implementation of the Finding Dory project, including the rationale, the goals, and the fingerprinting localization process.

Table of Content

Introduction

The execution of the project can be summarized with the following steps:

1. **Data extraction**: the procedure of getting the measurements from the server
2. **Data analysis**: this step of the process involves many steps. First we cleaned the data, then we analyzed it to build the dataset and to improve the process of data retrieval, since some measurements could only be found by exploiting informations retrieved from the server.
3. **Localization**: Once we built the dataset we processed the data by merging observations coming from the same coordinates, approximating the missing values and then we computed a possible position of Dory basing on its RSSI readings plus the fingerprinting database.



Data Extraction

MQTT

As for the tools emplyed we used python with the paho mqtt library to contact the server and retrieve data. The script first establishes a connection to the server, then subscribes to all avalaible topics using the `#` metacharacter, and lastly it listens for exactly 60 minutes. Every message received is saved as a dictionary in a JSON file with the following syntax:

```
msg = {
        "topic": message.topic,
        "payload": message.payload.decode("utf-8"),
        "qos": message.qos,
        "retain": message.retain,
}
```

Where `Message` is an object of the `paho-mqtt` library which contains newly received messages from the MQTT client. This format is suited to be analyzed with python later on.

A quite long listen time was necessary because the data relative to the $(8.0, 4.0)$ position had a low periodicity, meaning that with shorter capture times it was not to be found. The result of the capture is then saved to the `data.json` file.

Some measurements were manually extreacted and used in later steps of the data extraction process because they contain valuable informations on COAP data retrieval, namely the following ones:

Topic	Payload
`coap/post/mixed/`	`?problem=memory`
`coap/post/mixed/`	`go to the Doctor of the BarrierReef`
`coap/lies`	`resources can be hidden, find all of them and you'll get a treasure`
`coap/hidden`	`find the HiddenTreasure in the BarrierReef`
`coap/resource`	`/root/BarrierReef/FishLocator?user=Dory`
`anemone/in/the/barrier/reef`	`/root/BarrierReef/Anemone?owner=Marlin`
`great/barrier/reef/with/post`	`/root/PostMe6?search=entry`
`other/coap/resource`	`/root/BarrierReef/Apps?fingerprint=True`
`other/coap/resource`	`&gps=False`
`other/coap/resource`	`wait for this A LOT!`

COAP

To retrieve COAP data we used mainly two tools: Firefox with Copper running on the course virtual machine, and tzolov/coap-shell. Using the latter we executed a `discover` request which exposed several resources, which we saved at `coap/resources.txt`. Then by exploiting the following MQTT message:

Topic	Payload
`coap/hidden`	`find the HiddenTreasure in the BarrierReef`

We manually added `/root/BarrierReef/HiddenTreasure` to the resource list.

Lastly for each available resource we performed a request for each COAP method type using Copper, with special care for resources which needed an `observe` request. We wrote down all interesting responses in a text file.

The result of both data extraction procedures is avalaible respectively at `mqtt/data.json` and `coap/coap_coords_raw.txt`.

Retrieving Dory's RSSI

Lastly we needed Dory RSSI measurement to apply our fingerprinting technique. To retrieve such values we used COAP and in particular we perform a `GET` request with the `observe` option marked to the `BarrierReef/Dory` resource. After some time we got the following response:

```
$ connect coap://131.175.120.117
available
$ observe coap://131.175.120.117:5683/root/BarrierReef/Dory
OBSERVE START coap://131.175.120.117coap://131.175.120.117:5683/root/BarrierReef/Dory
```

After some time we got the following response:

```
coap://131.175.120.117:5683/root/BarrierReef/Dory
Dory just remembered her RSSI vector: [-57,-63,-58,-64,-63,-66]
```

Which was exactly what we needed to finished the data extraction process.

Data Analysis

The data analysis steps are carefully documented in the `localization.ipynb` Jupyter Notebook. The steps involved in the process are the following:

Cleaning Data

MQTT Regarding MQTT we used python to delete repeated entries and delete invalid ones, such as entries with invalid coordinates or RSSI parameters, resulting in 14 valid unique observations saved in the `mqtt_coords.txt` file. The scripts used to analyze the data are available in the `mqtt` subdirectory.

First we removed duplicates:

```
def remove_duplicates(data):
    res = []
    for msg in data:
        if msg not in res:
            res.append(msg)
    return res
```

Then we performed the following checks for each entry:

- Check that the entry actually contains a valid payload of the form `x,y | rssi_A1 | ... | rssi_A6`.
- Check that the data is valid, i.e. it's numerical data with reasonable values

To achieve that we used python `re` regex library:

```
for msg in data:
        if msg["payload"].count("|") == 6:

            coords_regex = r"(\d{1,2}\.0),(\d{1,2}\.0)"
            rssi_regex = r"\|(-?\d+),(-?\d+),(-?\d+),(-?\d+),(-?\d+)"

            if search(coords_regex, msg["payload"]) is None or
                search(rssi_regex, msg["payload"]) is None:
```

```
        continue

    x = float(findall(coords_regex, msg["payload"])[0][0])
    y = float(findall(coords_regex, msg["payload"])[0][1])
    if x > bounds[1] or
        x < bounds[0] or
      y > bounds[1] or
      y < bounds[0]:
        continue

    rssi = findall(rssi_regex, msg["payload"])
    for i in range(len(rssi)):
        rssi[i] = int(rssi[i][0])
        if rssi[i] < -100 or rssi[i] > -1:
            continue
    res.append(msg)
```

COAP COAP instead required manual analysis. We parsed the entries marked as useful in the `coap_coords_raw.txt` source file with a python script to make it into a format more suitable for later processing. This process was mostly manual; this was an intentional process decision due to the high diversity and low numerosity of the CoAP responses.

Importing data

First we created two dataframes containing the values from the MQTT and COAP observations:

```
...
df_mqtt = pd.DataFrame(
  data=data_mqtt,
  columns=["X", "Y", "exp_id", "A1", "A2", "A3", "A4", "A5", "A6"]
)
...
df_coap = pd.DataFrame(
  data=data_coap,
  columns=["X", "Y", "exp_id", "A1", "A2", "A3", "A4", "A5", "A6"]
)
```

Then we merged them in a unique dataset:

```
df = pd.concat([df_coap, df_mqtt])

# manually define Dory's RSSI
Dory_RSSI = [-57,-63,-58,-64,-63,-66]
Dory_RSSI_np = np.array(Dory_RSSI)

# dataset constraints to check if the data is valid
assert(len(df) == 6*6*5)
assert(df.isna().sum().sum() == 0)

display(df)
```

In this schema, the column `exp_id` identifies the experiment during which a reading was acquired. In the available fingerprints there were five distinct experiments.

The set of all fingerprints counts 180 entries and can be found in `data/raw_data.csv`

Processing data

At this point of the process we had a reasonable dataset, but we still ran into some issues. First of all our dataset did not contain unique measurements but instead for each coordinate we had 5 different RSSI values. Moreover our dataset only contained measurements relative to even positions of the grid, but Dory could also be found in odd positions, so we needed a way to account for missing values. This part of the data analysis process is divided into two steps:

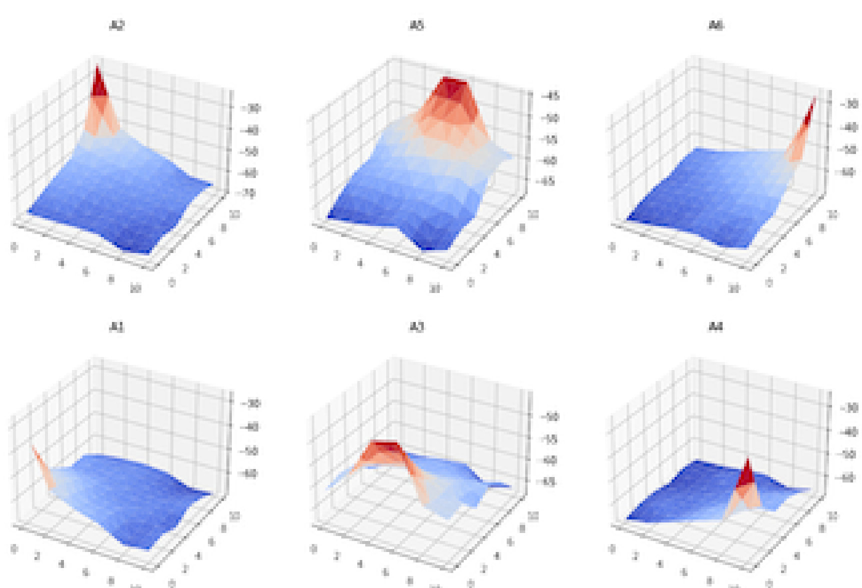
1. For each measurement, we computed the average of all 5 of its instances. The result was a new dataset with unique coordinates for each row.

```
means_data = []
for x in range(0,11,2):
    for y in range(0,11,2):
      row = [x,y]
      row += df.loc[(df['X'] == x) & (df['Y'] == y)
         .mean()[["A1", "A2","A3","A4","A5","A6"]].values.tolist()
      means_data.append(row)
df_means = pd.DataFrame(
  data=means_data,
  columns=['X', 'Y', "A1", "A2", "A3", "A4", "A5", "A6"]
)
```

2. Then we interpolated the values belonging to the missing coordinates.

   - If the position was not in the original dataframe and its adjacent positions were present, the corresponding entry is the average of the adjacent entries from the original dataframe (**linear interpolation**).
   - If the position was not in the original dataframe and its adjacent positions were also not present, the corresponding entry is the average of the adjacent entries computed in the new dataframe dataframe (**bilinear interpolation**).

   We also plotted the signal strength curve for visual inspection of any evident mistake:



The plots above shows reasonable signals for wifi RSSI propagation.

Localization

We will show two analysis approaches.

- **Pure mathematical**: We computed the euclidean distances of all produced data points from the reference RSSI and selected the minimum distance one.
- **Machine Learning**: We used all available fingerprints to train a KNN model, which we then use to classify the reference RSSI; the produced results are aggregated with a truncated weighted average.

Pure mathematical approach

Now that we have managed to average the values of repeated measurements and to approximate the missing ones, we can compute the Euclidean distance of each fingerprint in the interpolated dataframe from the Dory RSSI sample.

```
def compute_euclidean_distance(row):
  return np.linalg.norm(Dory_RSSI_np - row[["A1", "A2", "A3", "A4", "A5", "A6"]])

df_interpolation['Euclidean Distance'] = df_interpolation.
    apply(compute_euclidean_distance, axis=1)
display(df_interpolation.nsmallest(10, 'Euclidean Distance', 'all'))
```

Visual inspection of the smallest computed euclidean distances shows reasonable values and clustering around similar coordinates. The coordinates which has the lowest Euclidean distance are $(2, 3)$:

x	y	A1	A2	A3	A4	A5	A6	Euclidean Distance
2	3	-56.3	-62.2	-57.8	-63.4	-62.8	-65.7	1.28841

Repeating the same operation for the original dataframe, with no interpolation and all individual samples, shows coherent results.

```
df['Euclidean Distance'] = df.apply(compute_euclidean_distance, axis=1)
display(df.nsmallest(10, 'Euclidean Distance', 'all'))
```

x	y	A1	A2	A3	A4	A5	A6	Euclidean Distance
2	4	-58	-61	-59	-64	-62	-65	2.828427

Machine learning approach

KNN Most of our approaches are based on KNN, as seen in class. The first two are sound from a ML-theoretical perspective, but fail to produce reasonable result. The last one produces a reasonable result, but presents critical flaws from ML theory.

ML-theoretical: Fingerprint dataset only We model the localization problem as a multiclass classification problem. We associate to each position a class and to each class al ground truth label. We build the labels with a simple bijective function `f(int, int) -> str` based on the `(x,y)` positions of each fingerprint. This creates 36 distinct classes for our 180 fingerprints. We then split train and test set with $\frac{1}{5}$ ratio and stratified sampling. This allows us to have a representative dataset in both training and testing.

The confusion matrix shows a reasonable behaviour for such a model with better than random guessing performance. The accuracy plot shows that precision drops as the number of neighbors inreases.

The critical flaw of this model is that it cannot identify any odd position. It's limited to the even positions present in the training set.

ML-theoretical: Interpolated dataset We model the localization problem like before. We consider each experiment as the set of measurements from each anchor, that is $36 = 6 \cdot 6 \cdot 1$ samples. We augment each experiment with linear and bilinear interpolations to produce $121 = 11 \cdot 11 \cdot 1$ data points for each experiment, including both odd and even positions. This produces $605 = 11 \cdot 11 \cdot 5$ data points from the entire dataset. We then proceed like before, with stratified sampling and reasonable train/test split, to produce representative datasets for training and testing.

The confusion matrix shows again performance better than random guessing and the accuracy tracking shows decreasing performance as more neighbors are considered. Producing a confusion matrix for 121-class KNN classification is computationally expensive on our laptops.

Training only KNN All ML-theoretical approaches failed in most of the performance metrics, plus they returned a value that is quite different from the one we got from the pure mathematical approach, which is $(2, 6)$.

Since the attempted KNN approaches are not giving satisfactory results mostly because of data scarcity, we attempted a different technique that resembles KNN. In particular we choose to replicate the KNN approach but instead of splitting the dataset to employ a standard machine learning technique, we choose to use the whole dataset for the testing part of the process.

In particular we took the average of all experiments for each position and then we filled in missing (odd) values with interpolations. This produces a set of 121 data points, exactly one for each class. This makes it impossible to use any proper ML technique, as train/test split is impossible. We train a KNN classifier on this entire dataset and ask it to predict Dory's position.

This always produces the same result for up to ten neighbors. This is not a good sign for a reasonable KNN model, but still it's exactly the same result as the pure mathematical approach described previously.

Conclusion

After retrieving and processing data from the server we proceeded to apply two different approaches in order to estimate Dory's position, a pure mathematical one and a Machine Learning based one. The final result is derived from a process that employed some strong assumptions such as the interpolation of missing values, and the application of the conventiona KNN algorithm gave unsatisfactory results.

Still, both attempt pointed in the same direction, giving us the same estimated position for Dory: $(2, 3)$, i.e. we can say with a certain degree of confidence that $(2, 3)$ is the real Dory's position.