Experiment_1

November 21, 2024

1 Experiment 1

A BiTCN Implementation that supports synthesized signals of arbitrary length and external datasets.

[1]:
```
__author__ = "JUN WEI WANG"
__email__ = "wjw_03@outlook.com"
```

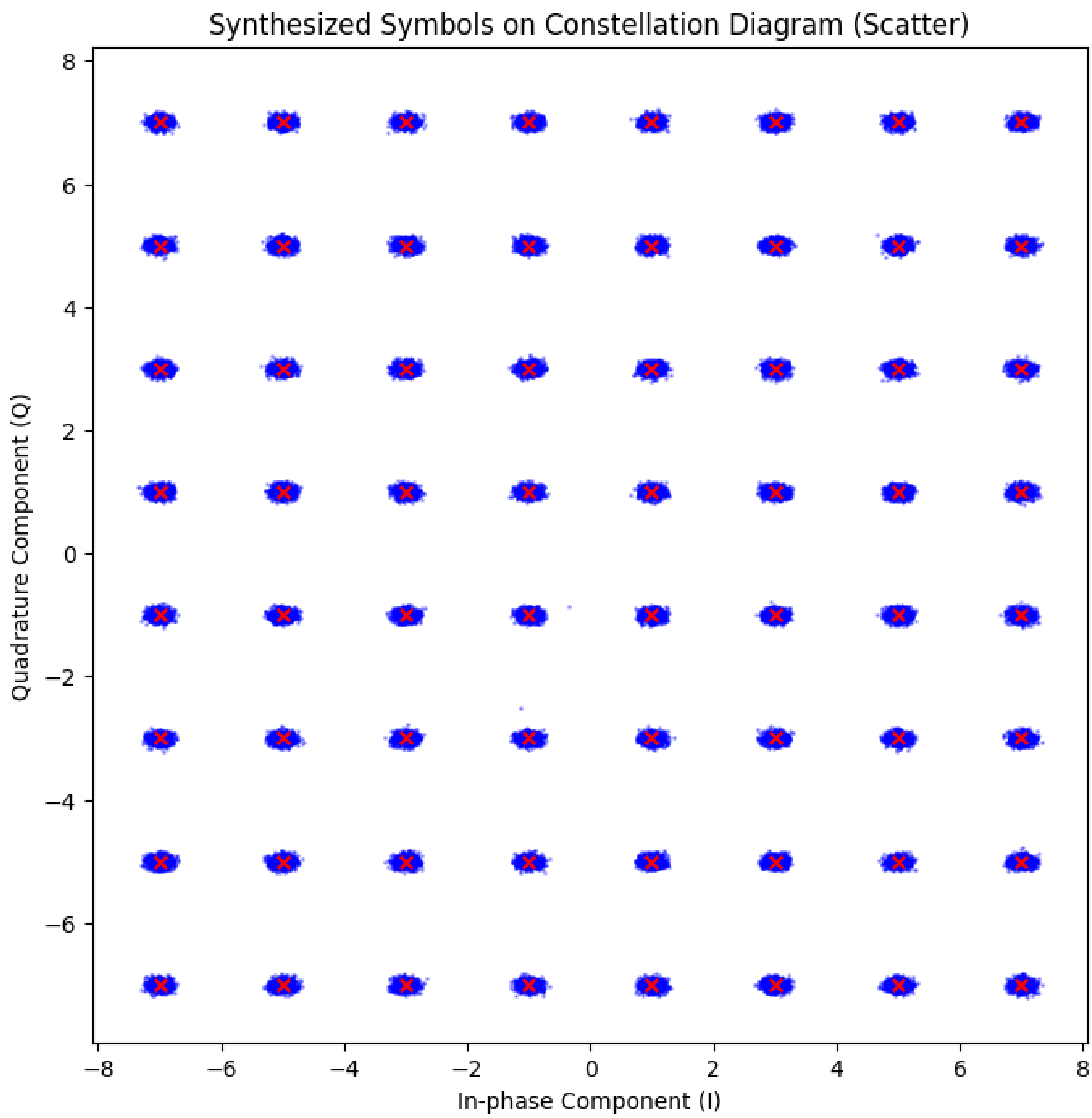
[2]:
```
import torch
import numpy as np
import os
from os import path

# Check for CUDA!
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Currently training on: {device}")

MODE = "TRAINING"
# MODE = "INFERENCE"

print(os.getcwd())
```

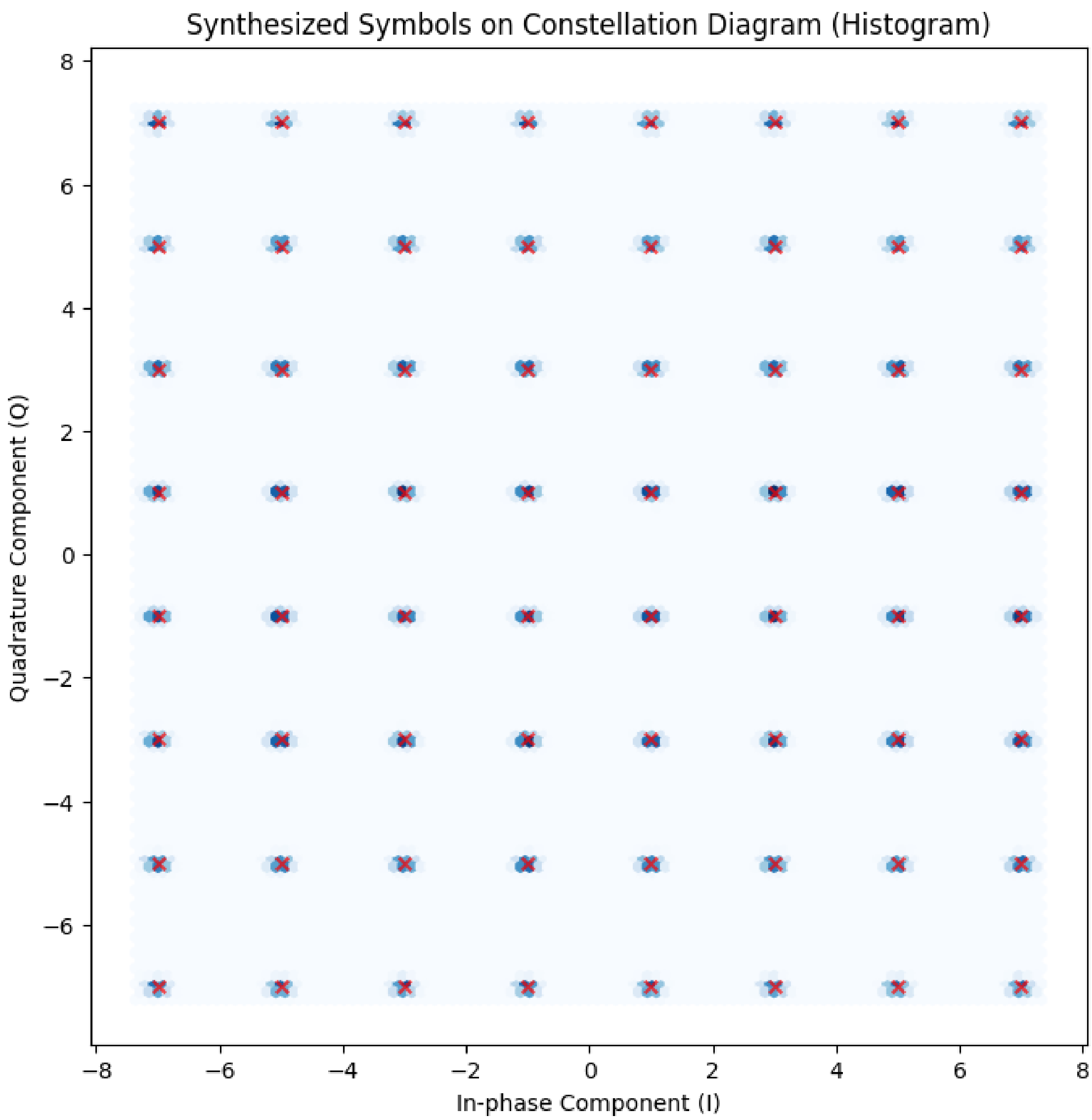
```
Currently training on: cuda
C:\Users\wjw_0\dsp-project
```

2 Data Generator

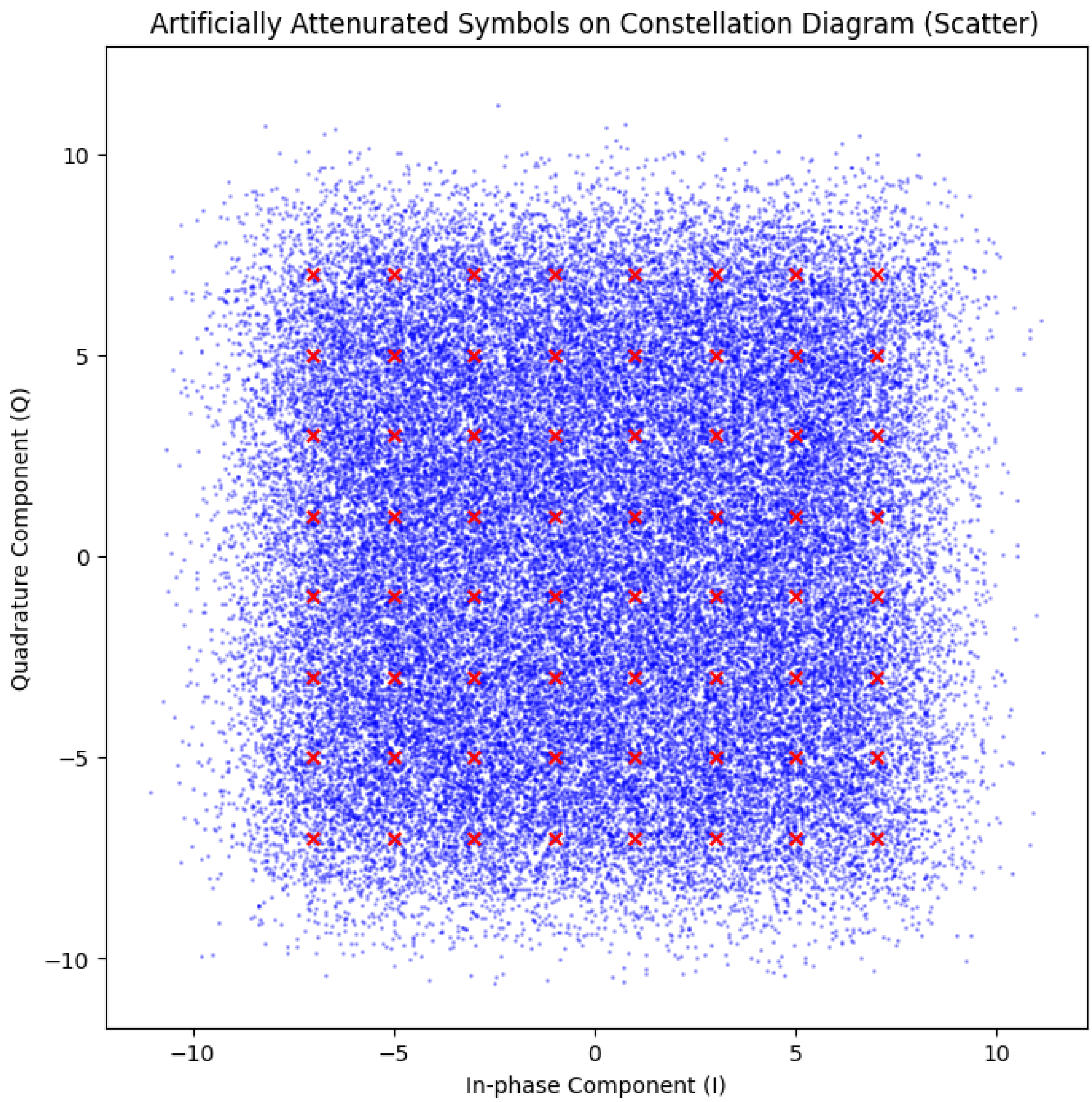
[3]:
```
import src.generator.QAM as QAM

SEED = 1
CONSTELLATION = "QAM"
QAM_ORDER = 64
NUMBEROFSYMBOLS = 51200

cons = QAM.read_constellation_file(QAM_ORDER, CONSTELLATION)

attenurated_data, original_data, raw_data, QAM_bits, preamble_data,␣
↪insertion_index = QAM.generate_seq(
```

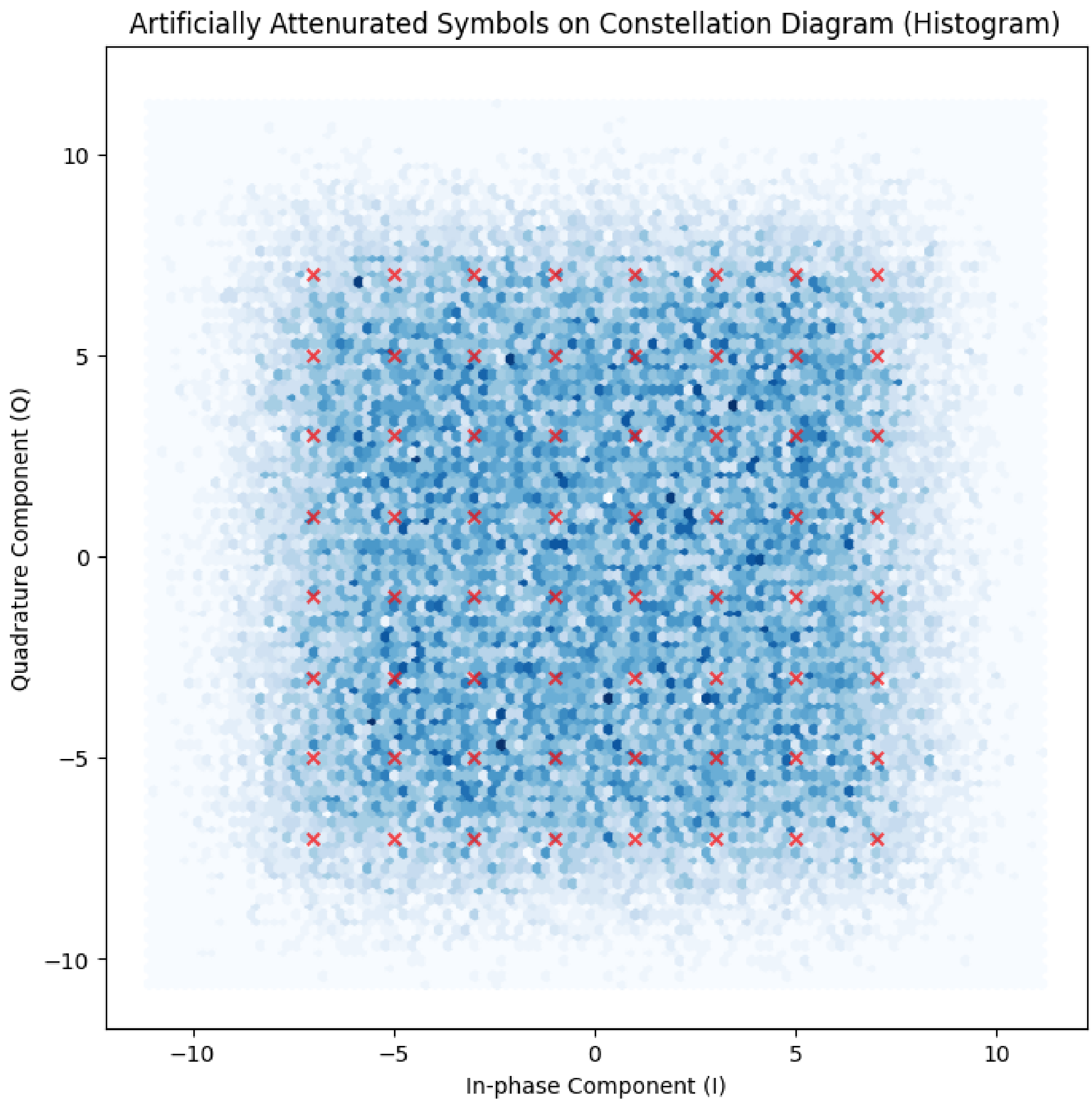
```python
    order=QAM_ORDER,
    cons=cons,
    num_symbols=NUMBEROFSYMBOLS,
    seed=SEED
)

og_demodulated_symbols, og_recoverdata = QAM.demodulation(
    original_data,
    NUMBEROFSYMBOLS,
    cons,
)

attenurated_data_demodulated_symbols, attenurated_data_recoverdata = QAM.
 ↪demodulation(
    attenurated_data,
    NUMBEROFSYMBOLS,
    cons,
)

QAM.graph_IQ_constellation(
    "Synthesized Symbols",
    og_recoverdata,
    cons
)

QAM.graph_IQ_constellation(
    "Artificially Attenurated Symbols",
    attenurated_data_recoverdata,
    cons
)
```


Synthesized Symbols on Constellation Diagram (Scatter)
Quadrature Component (Q)
In-phase Component (I)
8
6
4
2
0
−2
−4
−6
−8
6
4
2
0
−2
−4
−6
8



Synthesized Symbols on Constellation Diagram (Histogram)
Quadrature Component (Q)
In-phase Component (I)
8
6
4
2
0
−2
−4
−6
−8


Artificially Attenurated Symbols on Constellation Diagram (Scatter)
Quadrature Component (Q)
In-phase Component (I)
10
5
0
−5
−10
−10
−5
0
5
10



3 Nerual Network

3.1 Initialize Constants, Dataset, and the NN Model

[4]:
```
import torch.nn as nn
from torch.optim.lr_scheduler import StepLR
from tqdm import tqdm

# Neural Network
from src.nn.TCNN import BiTCN

# Dataset Tools
```

```python
from torch.utils.data import DataLoader
from src.data.dataset import CustomDataset
```

[5]:
```python
# CONSTANTS
NN_MODEL = "BiTCN"
TARGET_DATASET = "471" #        SYNTH
# TARGET_DATASET = "SYNTH"
MODEL_EXT = "pth"
MODEL_FILENAME = f"{NN_MODEL}_best_{TARGET_DATASET}.{MODEL_EXT}"

TRAIN_RATIO = 0.6

################################################################################
###########                     PARAMETERS                   ##################
################################################################################

BATCH_SIZE = 512 # used to be 512
WINDOW_SIZE = 256

# Trainning parameters
DROPOUT = 0.00
N_EPOCHS = 10
LEARNING_RATE = 3e-4

# Network parameters
INPUT_SIZE = 1
OUTPUT_SIZE = 1
CHANNEL_SIZES = [32] * 4
KERNEL_SIZE = 16
```

3.2 Load Dataset

[6]:
```python
DATASET_FOLDER = "dataset"

REAL_DATA_H = lambda x : f"data64QAM.txt"   # HOT-ENCODE
REAL_DATA = lambda x : f"OSC_sync_{x}.txt"
SYNTH_DATA = lambda x : f"SYNC_{x}.txt"
# NOTE: But for synthesized data, we can use our data generator implemented␣
↪above

dataset: torch.utils.data.Dataset = None

try:
    if TARGET_DATASET == "SYNTH":
        # Using synthesized data, no need to read any files
        try:
            attenurated_data
```

```
            original_data
        except:
            raise "Please run data generation"
        # print(attenurated_data.reshape(-1, 1))
        dataset = CustomDataset(None, win_len=WINDOW_SIZE)
        datas, labels = dataset.split_sequence(
            attenurated_data.reshape(-1, 1),
            original_data.reshape(-1, 1),
            WINDOW_SIZE
        )
        size = len(attenurated_data)
        dataset.dataset, dataset.labels, dataset.size = \
            torch.tensor(datas, dtype=torch.float32), \
            torch.tensor(labels, dtype=torch.float32), \
            size
        pass
    elif type(int(TARGET_DATASET)) == int:
        # Read data from dataset
        dataset = CustomDataset(
            DATASET_FOLDER,
            REAL_DATA(int(TARGET_DATASET)),
            REAL_DATA_H(-1),
            WINDOW_SIZE
        )
except ValueError:
    raise("Invalid target dataset")

print(f"{TARGET_DATASET} dataset loaded")
print(f"Dataset length: {len(dataset)} | Size: {dataset.size}")

# Split into train and validation sets

train_size = int(TRAIN_RATIO * len(dataset))
print(f"Traning ratio (train:valid): {TRAIN_RATIO}:{1 - TRAIN_RATIO}")
print(f"Training size: {train_size} | Validation size: {len(dataset) -␣
↪train_size}")
val_size = len(dataset) - train_size
train_dataset, val_dataset = torch.utils.data.random_split(
    dataset, [train_size, val_size]
)

# Setup the training and validation data loaders
train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=BATCH_SIZE, shuffle=False)
```

```
471 dataset loaded
Dataset length: 204545 | Size: 204800
Traning ratio (train:valid): 0.6:0.4
```

```
Training size: 122727 | Validation size: 81818
```

3.3 Load Model

[7]:
```python
model: torch.nn.Module = None

if NN_MODEL == "BiTCN":
    model = BiTCN(
        INPUT_SIZE,
        OUTPUT_SIZE,
        CHANNEL_SIZES,
        KERNEL_SIZE,
        seq_len=WINDOW_SIZE,
        dropout=DROPOUT
    )
else:
    raise("Model is not defined!")


print(f"{NN_MODEL} Model successfully Loaded")
model.to(device)
```

```
BiTCN Model successfully Loaded
```

[7]:
```
BiTCN(
  (tcn): TemporalConvNet(
    (network): Sequential(
      (0): TemporalBlock(
        (conv1): ParametrizedConv1d(
          1, 32, kernel_size=(16,), stride=(1,), padding=(15,)
          (parametrizations): ModuleDict(
            (weight): ParametrizationList(
              (0): _WeightNorm()
            )
          )
        )
        (chomp1): Chomp1D()
        (relu1): PReLU(num_parameters=1)
        (dropout1): Dropout(p=0.0, inplace=False)
        (conv2): ParametrizedConv1d(
          32, 32, kernel_size=(16,), stride=(1,), padding=(15,)
          (parametrizations): ModuleDict(
            (weight): ParametrizationList(
              (0): _WeightNorm()
            )
          )
        )
        (chomp2): Chomp1D()
```

```
    (relu2): PReLU(num_parameters=1)
    (dropout2): Dropout(p=0.0, inplace=False)
    (net): Sequential(
      (0): ParametrizedConv1d(
        1, 32, kernel_size=(16,), stride=(1,), padding=(15,)
        (parametrizations): ModuleDict(
          (weight): ParametrizationList(
            (0): _WeightNorm()
          )
        )
      )
      (1): Chomp1D()
      (2): PReLU(num_parameters=1)
      (3): Dropout(p=0.0, inplace=False)
      (4): ParametrizedConv1d(
        32, 32, kernel_size=(16,), stride=(1,), padding=(15,)
        (parametrizations): ModuleDict(
          (weight): ParametrizationList(
            (0): _WeightNorm()
          )
        )
      )
      (5): Chomp1D()
      (6): PReLU(num_parameters=1)
      (7): Dropout(p=0.0, inplace=False)
    )
    (downsample): Conv1d(1, 32, kernel_size=(1,), stride=(1,))
    (relu): PReLU(num_parameters=1)
  )
  (1): TemporalBlock(
    (conv1): ParametrizedConv1d(
      32, 32, kernel_size=(16,), stride=(1,), padding=(30,), dilation=(2,)
      (parametrizations): ModuleDict(
        (weight): ParametrizationList(
          (0): _WeightNorm()
        )
      )
    )
    (chomp1): Chomp1D()
    (relu1): PReLU(num_parameters=1)
    (dropout1): Dropout(p=0.0, inplace=False)
    (conv2): ParametrizedConv1d(
      32, 32, kernel_size=(16,), stride=(1,), padding=(30,), dilation=(2,)
      (parametrizations): ModuleDict(
        (weight): ParametrizationList(
          (0): _WeightNorm()
        )
```

```
    )
  )
  (chomp2): Chomp1D()
  (relu2): PReLU(num_parameters=1)
  (dropout2): Dropout(p=0.0, inplace=False)
  (net): Sequential(
    (0): ParametrizedConv1d(
      32, 32, kernel_size=(16,), stride=(1,), padding=(30,), dilation=(2,)
      (parametrizations): ModuleDict(
        (weight): ParametrizationList(
          (0): _WeightNorm()
        )
      )
    )
    (1): Chomp1D()
    (2): PReLU(num_parameters=1)
    (3): Dropout(p=0.0, inplace=False)
    (4): ParametrizedConv1d(
      32, 32, kernel_size=(16,), stride=(1,), padding=(30,), dilation=(2,)
      (parametrizations): ModuleDict(
        (weight): ParametrizationList(
          (0): _WeightNorm()
        )
      )
    )
    (5): Chomp1D()
    (6): PReLU(num_parameters=1)
    (7): Dropout(p=0.0, inplace=False)
  )
  (relu): PReLU(num_parameters=1)
)
(2): TemporalBlock(
  (conv1): ParametrizedConv1d(
    32, 32, kernel_size=(16,), stride=(1,), padding=(60,), dilation=(4,)
    (parametrizations): ModuleDict(
      (weight): ParametrizationList(
        (0): _WeightNorm()
      )
    )
  )
  (chomp1): Chomp1D()
  (relu1): PReLU(num_parameters=1)
  (dropout1): Dropout(p=0.0, inplace=False)
  (conv2): ParametrizedConv1d(
    32, 32, kernel_size=(16,), stride=(1,), padding=(60,), dilation=(4,)
    (parametrizations): ModuleDict(
      (weight): ParametrizationList(
```

```
          (0): _WeightNorm()
        )
      )
    )
    (chomp2): Chomp1D()
    (relu2): PReLU(num_parameters=1)
    (dropout2): Dropout(p=0.0, inplace=False)
    (net): Sequential(
      (0): ParametrizedConv1d(
        32, 32, kernel_size=(16,), stride=(1,), padding=(60,), dilation=(4,)
        (parametrizations): ModuleDict(
          (weight): ParametrizationList(
            (0): _WeightNorm()
          )
        )
      )
      (1): Chomp1D()
      (2): PReLU(num_parameters=1)
      (3): Dropout(p=0.0, inplace=False)
      (4): ParametrizedConv1d(
        32, 32, kernel_size=(16,), stride=(1,), padding=(60,), dilation=(4,)
        (parametrizations): ModuleDict(
          (weight): ParametrizationList(
            (0): _WeightNorm()
          )
        )
      )
      (5): Chomp1D()
      (6): PReLU(num_parameters=1)
      (7): Dropout(p=0.0, inplace=False)
    )
    (relu): PReLU(num_parameters=1)
  )
  (3): TemporalBlock(
    (conv1): ParametrizedConv1d(
      32, 32, kernel_size=(16,), stride=(1,), padding=(120,), dilation=(8,)
      (parametrizations): ModuleDict(
        (weight): ParametrizationList(
          (0): _WeightNorm()
        )
      )
    )
    (chomp1): Chomp1D()
    (relu1): PReLU(num_parameters=1)
    (dropout1): Dropout(p=0.0, inplace=False)
    (conv2): ParametrizedConv1d(
      32, 32, kernel_size=(16,), stride=(1,), padding=(120,), dilation=(8,)
```

```
          (parametrizations): ModuleDict(
            (weight): ParametrizationList(
              (0): _WeightNorm()
            )
          )
        )
        (chomp2): Chomp1D()
        (relu2): PReLU(num_parameters=1)
        (dropout2): Dropout(p=0.0, inplace=False)
        (net): Sequential(
          (0): ParametrizedConv1d(
            32, 32, kernel_size=(16,), stride=(1,), padding=(120,),
dilation=(8,)
            (parametrizations): ModuleDict(
              (weight): ParametrizationList(
                (0): _WeightNorm()
              )
            )
          )
          (1): Chomp1D()
          (2): PReLU(num_parameters=1)
          (3): Dropout(p=0.0, inplace=False)
          (4): ParametrizedConv1d(
            32, 32, kernel_size=(16,), stride=(1,), padding=(120,),
dilation=(8,)
            (parametrizations): ModuleDict(
              (weight): ParametrizationList(
                (0): _WeightNorm()
              )
            )
          )
          (5): Chomp1D()
          (6): PReLU(num_parameters=1)
          (7): Dropout(p=0.0, inplace=False)
        )
        (relu): PReLU(num_parameters=1)
      )
    )
  )
  (linear): Linear(in_features=16384, out_features=1, bias=True)
)
```

3.4 Training

[8]:
```
def train(model, device,train_loader, optimizer, criterion):
    model.train()
    total_loss = 0
    for X_batch, y_batch in tqdm(train_loader, desc="Training", leave=False):
        optimizer.zero_grad()
        output = model(X_batch.to(device))
        loss = criterion(output, y_batch.to(device))
        loss.backward()
        optimizer.step()
        total_loss += loss.item()
        average_loss = total_loss / len(train_loader)
    return average_loss

def validate(model, device, val_loader, criterion):
    model.eval()
    total_loss = 0
    with torch.no_grad():
        for X_batch, y_batch in tqdm(val_loader, desc="Validation",␣
 ↪leave=False):
            output = model(X_batch.to(device))
            loss = criterion(output, y_batch.to(device))
            total_loss += loss.item()
        average_loss = total_loss / len(val_loader)
    return average_loss

if MODE == "TRAINING":
    criterion = nn.MSELoss()
    optimizer = torch.optim.Adam(
    model.parameters(),
    lr = LEARNING_RATE
    )
    scheduler = StepLR(optimizer, step_size=3, gamma=0.1)

    # Train the model
    train_losses = []
    val_losses = []

    best_val_loss = float('inf')

    for epoch in range(N_EPOCHS):
        print(f"Starting epoch {epoch + 1}/{N_EPOCHS}")

        train_loss = train(model, device, train_loader, optimizer, criterion)
        val_loss = validate(model, device, val_loader, criterion)
        train_losses.append(train_loss)
```

```
        val_losses.append(val_loss)
        scheduler.step()

        print(f"Epoch [{epoch + 1}/{N_EPOCHS}], Train Loss: {train_loss:.4f},␣
↪Validation Loss: {val_loss:.4f}")
        if val_loss < best_val_loss:
            best_val_loss = val_loss
            torch.save(model.state_dict(), MODEL_FILENAME)
            print(f"Saved model with validation loss: {best_val_loss:.4f}")
```

```
Starting epoch 1/10


Epoch [1/10], Train Loss: 0.3957, Validation Loss: 0.0345
Saved model with validation loss: 0.0345
Starting epoch 2/10


Epoch [2/10], Train Loss: 0.0246, Validation Loss: 0.0191
Saved model with validation loss: 0.0191
Starting epoch 3/10


Epoch [3/10], Train Loss: 0.0169, Validation Loss: 0.0145
Saved model with validation loss: 0.0145
Starting epoch 4/10


Epoch [4/10], Train Loss: 0.0137, Validation Loss: 0.0137
Saved model with validation loss: 0.0137
Starting epoch 5/10


Epoch [5/10], Train Loss: 0.0134, Validation Loss: 0.0134
Saved model with validation loss: 0.0134
Starting epoch 6/10


Epoch [6/10], Train Loss: 0.0132, Validation Loss: 0.0132
Saved model with validation loss: 0.0132
Starting epoch 7/10


Epoch [7/10], Train Loss: 0.0130, Validation Loss: 0.0132
Saved model with validation loss: 0.0132
Starting epoch 8/10
```

```
Epoch [8/10], Train Loss: 0.0129, Validation Loss: 0.0132
Saved model with validation loss: 0.0132
Starting epoch 9/10


Epoch [9/10], Train Loss: 0.0129, Validation Loss: 0.0132
Saved model with validation loss: 0.0132
Starting epoch 10/10


Epoch [10/10], Train Loss: 0.0129, Validation Loss: 0.0131
Saved model with validation loss: 0.0131
```

3.5 Inference

[9]:
```python
from tqdm import tqdm
from torch.utils.data import DataLoader
import math

from src.data.dataset import CustomDataset
from src.nn.TCNN import BiTCN

# Load the model
model = BiTCN(
    INPUT_SIZE,
    OUTPUT_SIZE,
    CHANNEL_SIZES,
    KERNEL_SIZE,
    seq_len=WINDOW_SIZE,
    dropout=DROPOUT
)
model = model.to(device)

model.load_state_dict(
    torch.load(MODEL_FILENAME, map_location=torch.device(device))
)

predictions = []

def inference(model, device, data_loader):
    model.eval()
    output=[]
    with torch.no_grad():
        import time
        i = 0
```

```
        for X_batch, y_batch in tqdm(data_loader, desc="Validation",␣
 ↪leave=False):
            out = model(X_batch.to(device))
            output.append(out.detach().cpu())
            outputs = torch.cat(output, dim=0)
            outputs_np = outputs.numpy()
    return outputs_np.flatten()

data_loader = DataLoader(dataset, batch_size=BATCH_SIZE, shuffle=False)

predictions = inference(model, device, data_loader)
half_window = math.floor((WINDOW_SIZE - 1) // 2)

og_data: np.ndarray = None

if TARGET_DATASET == "SYNTH":
    og_data = original_data
else:
    with open(path.join(os.getcwd(), "dataset", REAL_DATA_H(-1)), 'r') as file:
        og_data = np.array([float(line.strip()) for line in file.readlines()])

diff = dataset.size - (len(predictions)  + half_window*2)
prefix = og_data[:half_window + diff]
suffix = og_data[-half_window:]
final_predictions = np.concatenate([prefix, predictions, suffix])
final_predictions = final_predictions.reshape(-1,1)
# final_predictions = final_predictions.astype(np.float16)

np.savetxt("pred.txt", final_predictions, delimiter="\n")
```

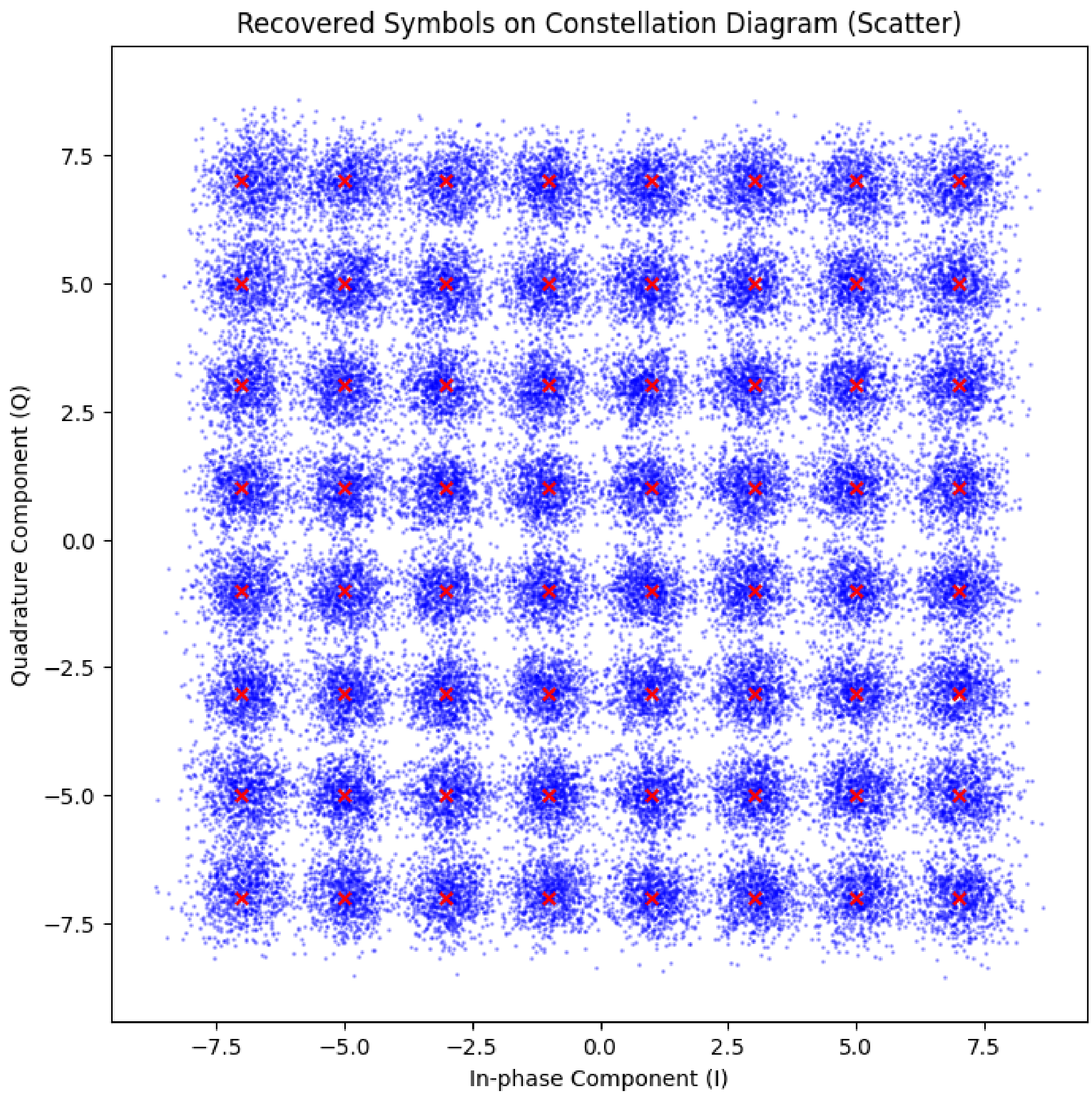
```
C:\Users\wjw_0\AppData\Local\Temp\ipykernel_39800\3700146736.py:20:
FutureWarning: You are using `torch.load` with `weights_only=False` (the current
default value), which uses the default pickle module implicitly. It is possible
to construct malicious pickle data which will execute arbitrary code during
unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
  torch.load(MODEL_FILENAME, map_location=torch.device(device))
Validation:   0%|
| 0/400 [00:00<?, ?it/s]
```

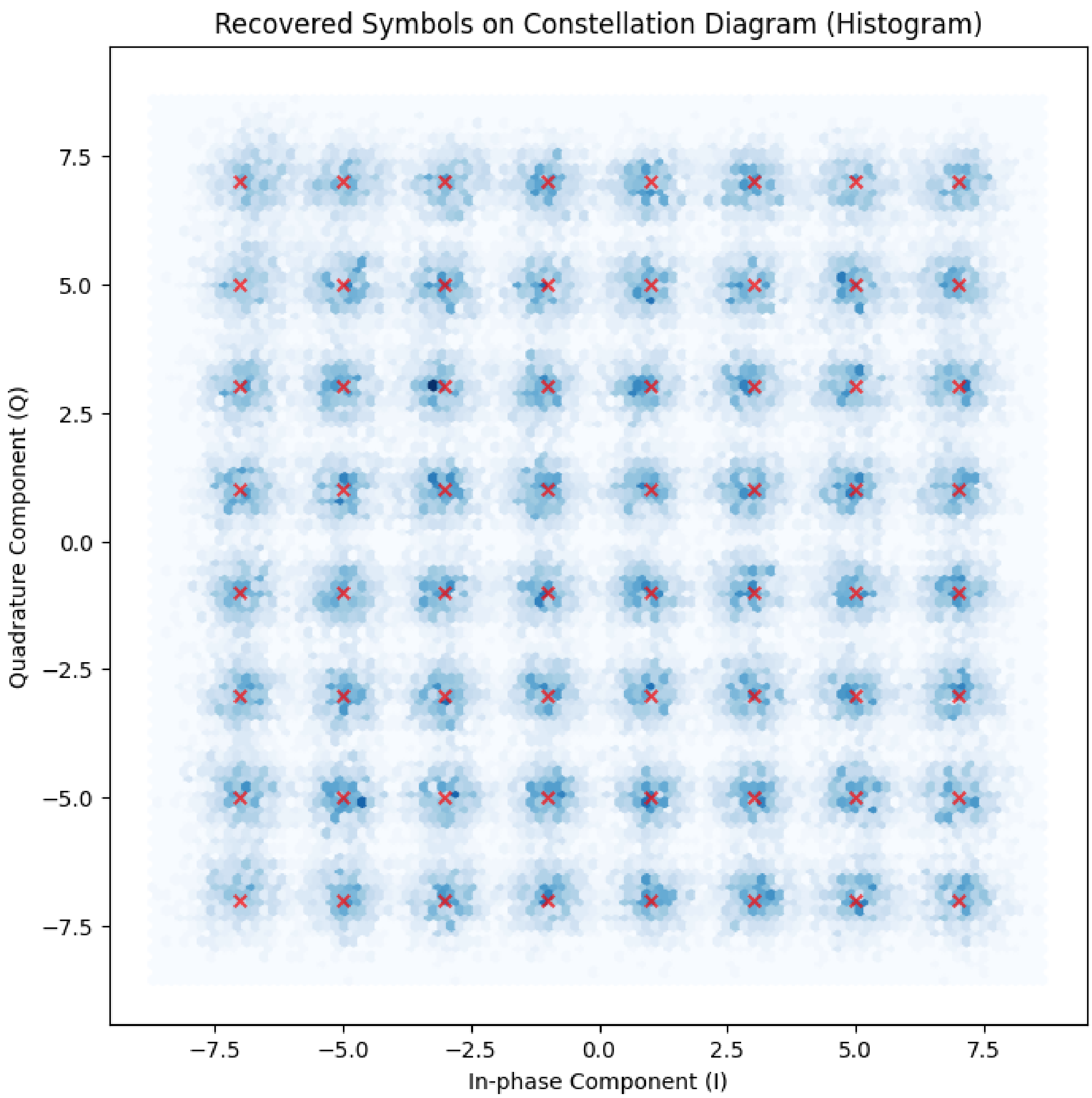
4 Post Processing

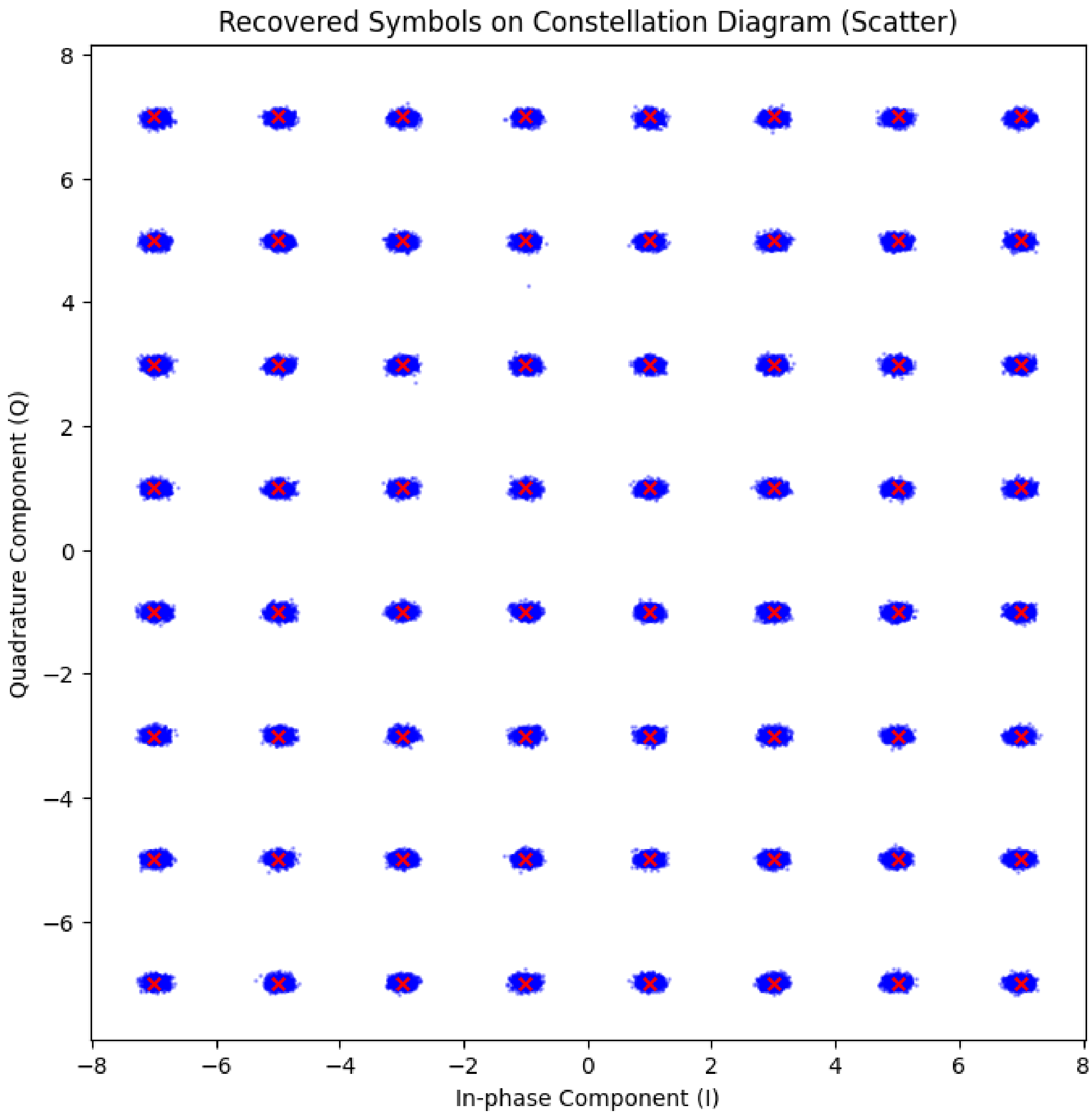
Demodulation & Visualization

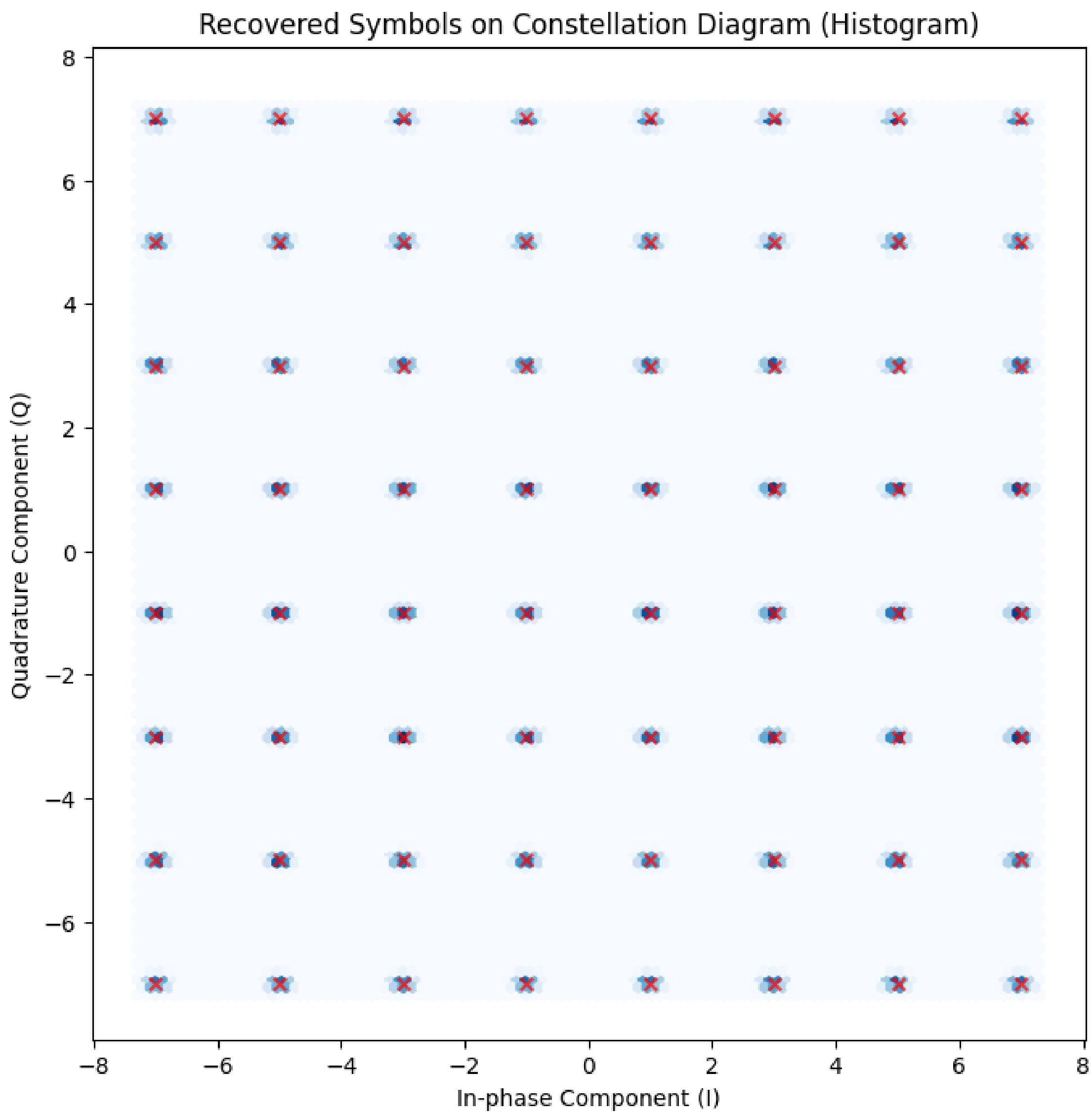
[22]:
```
cons = QAM.read_constellation_file(QAM_ORDER, CONSTELLATION)

demodulated_symbols, recoverdata = QAM.demodulation(
    final_predictions,
    NUMBEROFSYMBOLS,
    cons
)

QAM.graph_IQ_constellation(
    "Recovered Symbols",
    recoverdata,
    cons
)



if TARGET_DATASET == "SYNTH":
    target = np.zeros(len(QAM_bits), dtype=int)
    for i, sample in enumerate(recoverdata):
        distances = np.abs(sample - cons)
        target[i] = np.argmin(distances)  # Find the nearest constellation point

    print(len(demodulated_symbols), len(target))
    print(demodulated_symbols[:10], target[:10])
    res = QAM.calculate_ber(demodulated_symbols, target, 35)
    print(f"BER: {res[1]}")
else:
    from src.data.file_handler import read_file
    from src.data.processing import parse_str

    data = parse_str(read_file(path.join(DATASET_FOLDER, REAL_DATA_H(-1))))
    data = torch.tensor(data, dtype=torch.float32)
    data = data.reshape(1, -1).flatten()

    # data = QAM.downsample(data, 4)

    temp1, temp2 = QAM.demodulation(
        data,
        NUMBEROFSYMBOLS,
        cons
    )

    QAM.graph_IQ_constellation(
        "Recovered Symbols",
        temp2,
```

```
        cons
    )

    print(demodulated_symbols[:10], temp1[:10])
    res = QAM.calculate_ber(demodulated_symbols, temp1, 35)
    print(f"BER: {res[1]}")
```




Recovered Symbols on Constellation Diagram (Histogram)
Quadrature Component (Q)
In-phase Component (I)
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5


Recovered Symbols on Constellation Diagram (Scatter)
Quadrature Component (Q)
In-phase Component (I)
8
6
4
2
0
−2
−4
−6
−8
−6
−4
−2
0
2
4
6
8

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