Wireless Networks

Assignment-4

Submitted By

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Part A

Preprocess the CSI For each subcarrier, there are 2 values real and imaginary indexed at even and odd indices, respectively. Read the CSI dataset files, remove the first 128 columns (CSI data from the legacy header), and remove the pilot and null subcarrier.

```
In [8]:
         def preprocess(dataset):
             #print(dataset)
             len_=dataset.shape[0]
             len_=int(abs(0.03*len_))
             # print(len_)
             dataset=(dataset).iloc[len_:-len_, 128:]
             label=pd.DataFrame((dataset)['headlabel'])
             (dataset)=(dataset).drop(columns=['timestamp', 'headlabel'], axis=1)
             (dataset).columns=range(len((dataset).columns))
             # remove null and pilot subcarriers
             (dataset)=(dataset).drop((dataset).columns[delete_idxs], axis=1)
             (dataset).columns=range(len((dataset).columns))
             # print(amp_result.shape)
             return dataset, label
         #Fiber
         P26_fiber_4, label1=preprocess(P26_fiber_4)
         P27_fiber_4, label2=preprocess(P27_fiber_4)
         P28_fiber_4,label3=preprocess(P28_fiber_4)
P29_fiber_4,label4=preprocess(P29_fiber_4)
         P30_fiber_4, label5=preprocess(P30_fiber_4)
         P26_wood_4, label6=preprocess(P26_wood_4)
         P27_wood_4, label7=preprocess(P27_wood_4)
         P28_wood_4,label8=preprocess(P28_wood_4)
P29_wood_4,label9=preprocess(P29_wood_4)
         P30_wood_4, label10=preprocess(P30_wood_4)
         P26_glass_4, label11=preprocess(P26_glass_4)
         P27_glass_4, label12=preprocess(P27_glass_4)
         P28_glass_4, label13=preprocess(P28_glass_4)
         P29_glass_4, label14=preprocess(P29_glass_4)
         P30_glass_4, label15=preprocess(P30_glass_4)
```

Part B & C

Compute the amplitude for each subcarrier using the equation amplitudes=sqrt(imaginary2+real2) + Denoise the CSI samples with Hampel filter, 1-D wavelet transform filter, and savgol filter.

```
def remove nan(matrix ):
      temp=marrix_.copy()
temp=temp.dropna()
temp=temp.reset_index(drop=True)
return temp
 def amplitude(df):
      amp=[]
d=np.array(df)
for j in range(len(d)):
    imaginary=[]
    real=[]
           reat=[]
# phases=[]
for i in range(len(d[j])):
    if i%2==0:
    print("Denoising completed")
return dwt
      from scipy.signal import savgol_filter
window_length=5
      window_tengvi=-
poly_order=2
smoothed_data=savgol_filter(df, window_length, poly_order)
smoothed_data= pd.DataFrame(smoothed_data)
      print('smooth')
return smoothed_data
  def ampdeno(dataset,label):
    amp_result= amplitude(P26_fiber_4)
    print(amp_result.shape)
amp_result= hampel_filter(np.asarray(amp_result), 1000)
amp_result= denoise(pd.bataframe(amp_result), 'db4')
amp_result= smooth(amp_result)
amp_result= pd.concat([amp_result, label], axis=1)
      amp_result= remove_nan(amp_result)
return amp_result
```

Part D

Create folders with filenames, for example, P 26 glass 4, and then create separate files for each head gesticulation and save them within the respective folder.

Part E & F

Preprocessing the data for training with few settings out strategy. Combine the CSI files of two materials for training and the CSI files of the remaining materials for testing.

For example, combine "wood" and "fiber" for training and "glass" for testing + Prepare the input data for training.

```
import os
import pandas as pd
training_materials=['fiber_4','wood_4']
testing_materials=['glass_4']
training_all_files=[]
testing_all_files=[]
main_folder_path='C:/Users/lbjki/Downloads/gesticulation_data'
participants=[f"P{i}" for i in range(26,31)]
for pid in participants:
    for oid in training_materials:
         folder=pid+"_"+oid+"_amp'
         file_path=os.path.join(main_folder_path,folder)
         for headlabel_data in os.listdir(file_path):
             final_file_path=os.path.join(file_path,headlabel_data)
             td=pd.read_csv(final_file_path)
             training_all_files.append(td)
training_data=pd.concat(training_all_files,axis=0)
training_data=training_data.reset_index(drop=True)
Y=training data['headlabel'
X=training_data.iloc[0:,0:-1]
#Select 100 best
selector=SelectKBest(f_classif,k=100)
csi_feature_100=selector.fit_transform(X,Y)
Y=pd.DataFrame(Y)
onehot_encoder=OneHotEncoder()
csi_headlabel=onehot_encoder.fit_transform(Y)
csi_feature_10X10=np.reshape(csi_feature_100,(csi_feature_100.shape[0],10,10))
csi_feature_10X10.shape
X_train=csi_feature_10X10
Y_train=csi_headlabel
for pid in participants:
    for oid in testing_materials:
    folder=pid+"_"+oid+"_amp"
         file_path=os.path.join(main_folder_path,folder)
         for headlabel_data in os.listdir(file_path):
             final_file_path=os.path.join(file_path,headlabel_data)
             td=pd.read_csv(final_file_path)
             testing_all_files.append(td)
testing data=pd.concat(testing all files.axis=0)
testing\_data = testing\_data \cdot reset\_index(drop = \textbf{True})
Y=testing data['headlabel']
X=testing_data.iloc[0:,0:-1]
#Select 100 best
selector=SelectKBest(f_classif,k=100)
csi_feature_100=selector.fit_transform(X,Y)
Y=pd.DataFrame(Y)
onehot_encoder=OneHotEncoder()
csi_headlabel=onehot_encoder.fit_transform(Y)
csi_feature_10X10=np.reshape(csi_feature_100,(csi_feature_100.shape[0],10,10))
csi_feature_10X10.shape
X\_test, X\_va^\top, Y\_test, Y\_val=train\_test\_split(csi\_feature\_10X10, csi\_headlabel, test\_size=0.2, random\_state=42)
Y_train=Y_train.toarray()
Y_val=Y_val.toarray()
```

Part G

Train the model.

```
In [20]:
          def csi_network_inc_res(input_sh, output_sh):
              nb_filters=64
              x_input=Input(input_sh)
              tcn1=TCN(
                  nb_filters=nb_filters,
                   nb_stacks=1,
                  kernel_size=3,
                  dilations=(1, 2, 4, 8, 16),
                  use_skip_connections=True,
                  use_layer_norm=True,
kernel_initializer='glorot_uniform'
              x=tcn1(x_input)
              print(f'TCN.receptive_field: {tcn1.receptive_field}.')
              x=tf.keras.layers.Flatten()(x)
              x=tf.keras.layers.Dense(output_sh, activation='relu', name='dense')(x)
              model=Model(inputs=x_input, outputs=x, name='csi_model')
              return model
In [21]:
          model=csi_network_inc_res((10, 10), 7)
          # Compile the model
          model.compile(
              optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
              loss='categorical_crossentropy',
              metrics=['accuracy']
          # Train the model
          model.fit(
              X_train,
              Y_train,
              batch_size=64,
              epochs=5,
              validation_data=[X_val, Y_val],
              callbacks=[
                  tf.keras.callbacks.ModelCheckpoint('checkpointmodel.keras',
                                                       monitor='val_accuracy',
                                                       save_best_only=True,
                                                       save_weights_only=False),
              ]
```

WARNING:tensorflow:From C:\Users\bjki\PycharmProjects\pythonProject\.venv\Lib\site-packages\keras\src\backend\tensorflow\core.py:204: The name tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

Part H

Few shot learning

```
WARNING:tensorflow:From C:\Users\lbjki\PycharmProjects\pythonProject\.venv\Lib\site-packages\keras\src\backend\tensorflow\cor
        e.py:204: The name tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.
        TCN.receptive_field: 48.
        Epoch 1/5
        963/963 -
                                     — 53s 39ms/step - accuracy: 0.1475 - loss: 10.1556 - val_accuracy: 0.1016 - val_loss: 8.0907
        Epoch 2/5
        963/963 -
                                     - 35s 36ms/step - accuracy: 0.1668 - loss: 10.0106 - val accuracy: 0.1954 - val loss: 5.4123
        Epoch 3/5
        963/963 -
                                     — 37s 38ms/step - accuracy: 0.2835 - loss: 5.9509 - val_accuracy: 0.1974 - val_loss: 5.4153
        Epoch 4/5
                                    — 44s 42ms/step - accuracy: 0.2822 - loss: 5.9717 - val_accuracy: 0.1954 - val_loss: 5.3959
        963/963 -
        Epoch 5/5
        963/963 -
                                    — 41s 43ms/step - accuracy: 0.2850 - loss: 5.9721 - val_accuracy: 0.1959 - val_loss: 5.4987
Out[21]: <keras.src.callbacks.history.History at 0x1f3147dbb30>
In [22]: model.evaluate(X_test, Y_test, verbose=0)
Out[22]: [5.54888391494751, 0.19157542288303375]
In [25]: from sklearn.model_selection import StratifiedShuffleSplit
          import time
          shot_sizes=[10,50,100,200,250,300,350,400,500,1000,2000,5000,10000]
          results=[]
          for numshots in shot_sizes:
               retrained\_model = tf.keras.models.clone\_model(model)
               retrained_model.set_weights(model.get_weights())
               retrained model.compile(
                   optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
                  loss='categorical_crossentropy',
                   metrics=['accuracy']
               stratified\_split=StratifiedShuffleSplit(test\_size=len(X\_test)-numshots,random\_state=42)
              for train_idx,test_idx in stratified_split.split(X_test,Y_test):
    few_shot_indices=train_idx
                   test_indices=test_idx
               X_FS=X_test[few_shot_indices]
               Y_FS=Y_test[few_shot_indices]
               X_test_new=X_test[test_indices]
              retrain_start_time=time.time()
retrained_model.fit(X_FS,Y_FS,batch_size=64,epochs=5,verbose=0)
               retrain_time=time.time()-retrain_start_time
               test_start_time=time.time()
               test\_loss, test\_accuracy = retrained\_model.evaluate(X\_test, Y\_test, verbose = 0)
               test time-time time()-test start time
```

Part I
Plotting changes in accuracy with the number of shots

