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Live Motion Direction Estimation

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Problem Statement

Correctly identifying camera motion from video feeds is integral for real world applications

- Self driving cars
- Stabilization of objects
- Trajectory mapping

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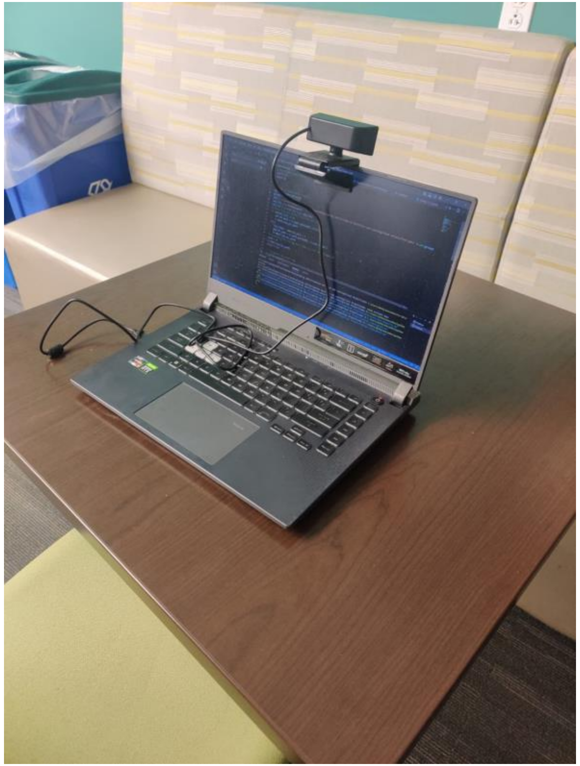
Data Collection

Dataset

- Consists of ~4000 images.
  - Videos were collected and converted to frames (images)
  - Images then converted into disparity maps

- Dataset has 5 classes
  - Each class is based on -
    - *Forward*
    - *Backward*
    - *Turning Left*
    - *Turning Right*
    - *Standing Still*

Dataset collection

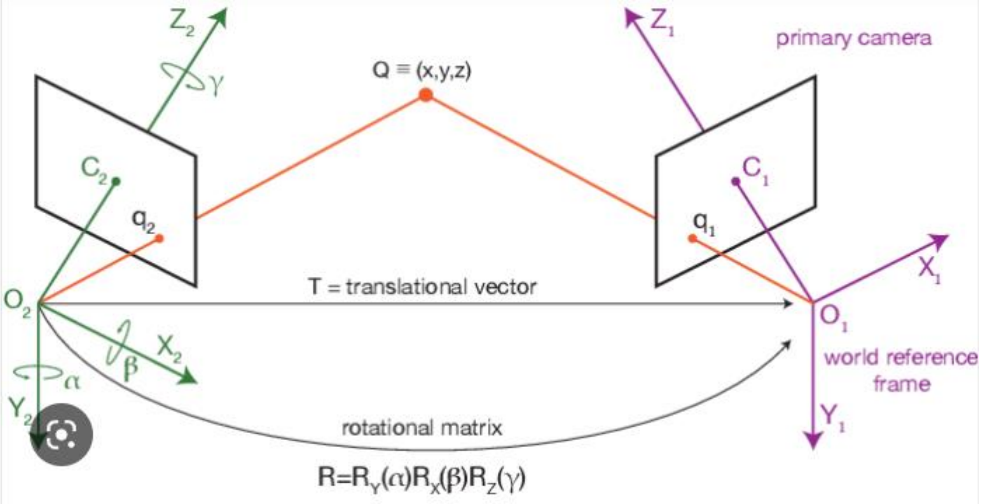


Feature Extraction

Feature Extraction: Frame Change Fundamentals

Capture Change in Movement:

- Process every 5th frame:
  - Allows for enough average change in pixels over the given period
  - Capture change in images over some translation to produce stereo image



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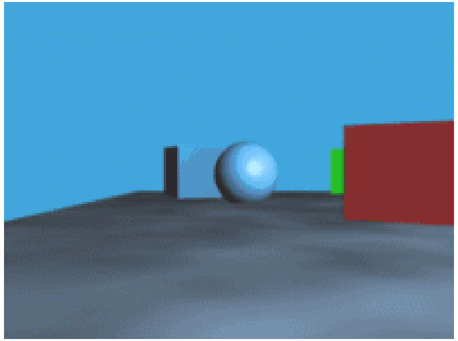
Feature Extraction: Disparity Maps



Disparity Map created from 2 images

- Loop through each test data class and each individual test number
  - Images were converted to grayscale first
  - CV2.stereoSGBM_create function used
    - *Parameters were played around with interactive tuning parameters*
    - *Tuning file given as stereo_vision_tuning.py*
    - *Final Parameters: numDisparities=16, blockSize=9*
  - Disparity Maps saved into respective folders

Why Disparity Map?

- Returns apparent pixel difference or motion between a pair of stereo images
- Normalizes the motion based on depth - Objects further shift less over time
- Estimating the behavior of disparity map across epipolar line - Learning

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Feature Extraction - Examples

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Classification Models

The Naive Bayes Classifier scored 74.7% accuracy on the test data.

- Preprocessing
  - Images were stored in folders according to their correct labels.
  - 2x2 max pooling block filter reduces overall size
  - Reshape the image to a vector of disparity values

- Model Parameters
  - Priors: none were used
  - Variance: $1x10^{-9}$
  - Training - 80 %
  - Testing - 20 %

Using Support Vector Classification yielded an accuracy score of 93%

- SVC - Multiclass Support Vector Machine (SVM)
- Preprocessing
  - Images were stored in folders according to their correct labels.
  - 2x2 max pooling block filter reduces overall size
  - Reshape the image to a vector of disparity values

- Model Parameters
  - Kernel: rbf
  - Degree of polynomial: 3
  - Tolerance: 0.001
  - Training - 80 %
  - Testing - 20 %

Using Linear Neural Networks yielded an accuracy score of 83%

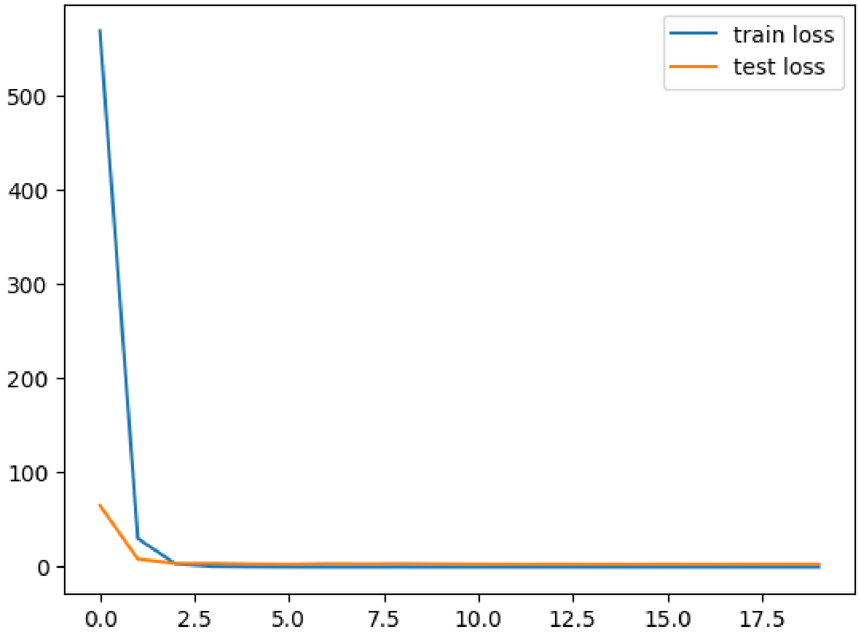
Preprocessing:

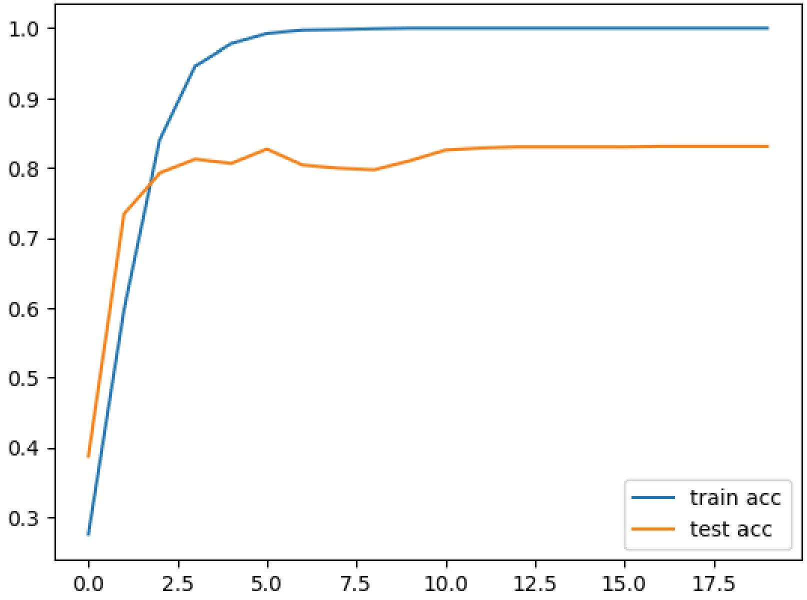
- Resizing image data to 300 x 300 pixels using Image library's resize method.
- Normalizing pixel values by dividing each by 255 to scale between 0 and 1.
- 46,966 images with corresponding labels split into 31,458 for training and 15,508 for testing using 67:33 split ratio.

Model Parameters:

- LinearModel is a feedforward neural network with 3 fully connected layers.
- Input image is flattened into 1D tensor before passing through the network.
- Output layer has 5 features, indicating a multi-class classification task.

Linear NN: Model Results over Epochs





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Classification Model: Convolutional Neural Network (CNN)

Preprocessing:

- Resized image from (480,640) to (300,300) to reduce dimensionality for quicker processing
- Loop over Disparity Map and place into tensor.
  - Concatenate with labels
- Set batch size to 100 per packet for CNN model

Model Parameters:

- 1 Input Channel: grayscale
- 3 hidden layers with ReLU and Pooling between each layer
- 2 Linear Layers with ReLU between each layer
- Cross Entropy Softmax layer to classify into 5 classes
- Run 20 epochs over dataset

Overfitting Problem!

- Implemented dropout to correct for overfitting! (0.2 dropout)

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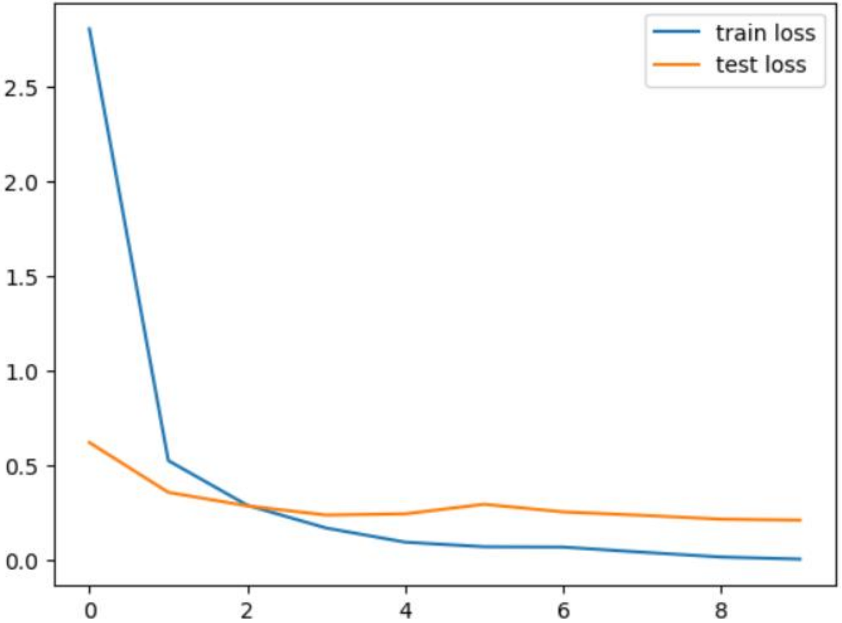
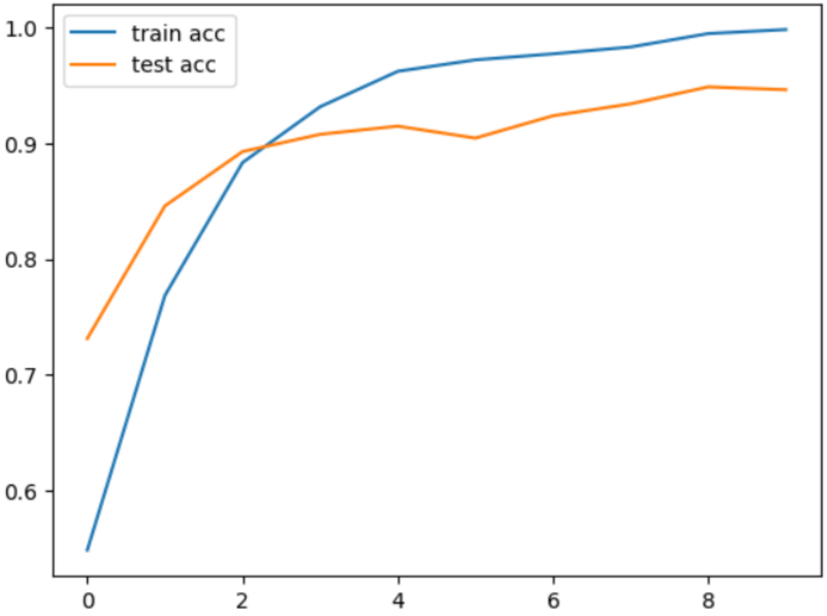
CNN: Model Results over Epochs



Loss for Train and Test over 20 Epochs



Accuracy for Train and Test over 20 Epochs

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Results

Results Across all Models

Model	Train Accuracy	Test Accuracy
Naive Bayes	-	74.7%
SVC	-	93%
Deep Neural Network	99%	83%
Convolutional Neural Network	98%	94.6%

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Conclusion: Results Ablation Study

SVC Vs Naive Bayes:

Formula:

$$P(\text{class} \mid \text{data}) = \frac{P(\text{data} \mid \text{class})\, P(\text{class})}{P(\text{data})}$$

- Holds a conditional independence assumption - Pixels can often tell neighboring pixels. Usually the same.

Look at SVC:

- SVC creates a soft margin for classification
- Performs worse for larger data sets
    - Noise in dataset will cause overfitting towards training data

DNN Vs CNN:

- As an image processing problem, best model aligns with CNN method
- DNN is more variant to noise in dataset and trains weights closer to training dataset.
    - Overfitting to dataset main concern
- CNN can learn better filters to create more accurate weights
- Vary Kernel size, stride to create different filter iteration

Live Motion Capture Prediction:

Code for Running this located in CNN_model notebook file

Observations:

- Top Red text shows current class
- Overall good performance.
- Slight jitter causes the class to change even when ground truth remains same

Future Improvements

- Add data augmentation to account for jitter
- Reinforce network by training on individual frames in addition to disparity map
- Regularization

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Code Snippets

Feature Extraction and Video Capture

Video Capture Loop

```
os.chdir(new_dir_path)
while(True):

    # Capture the video frame
    # by frame
    ret, frame = vid.read()

    # Display the resulting frame
    cv2.imshow('frame', frame)
    cv2.imwrite('Frame'+str(count)+'.jpg', frame)
    count = count + 1


    # the 'q' button is set as the
    # quitting button you may use any
    # desired button of your choice
    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

# After the loop release the cap object
vid.release()
# Destroy all the windows
cv2.destroyAllWindows()
```

Feature Extraction
Snippet of full file

```
# Function gets disparity map by comparing every 5 images
def get_disparity_map_test(path, class_type):
    # Get correct directory
    dir_list = os.listdir(path)
    dir_list = np.array(dir_list)
    class_dir = 'C:/Users/aksha/OneDrive/Desktop/Desktop/Spring 2023/Estimatio
    class_dir = class_dir + '/' + class_type + '/disp'
    count = 0
    # Loop through each test case
    for i in range(len(dir_list)-5):
        # Get image path for every 5th image and compare
        frame_num_1 = dir_list[i]
        frame_num_2 = dir_list[i+5]
        path_1 = path + '/' + frame_num_1
        path_2 = path + '/' + frame_num_2
        gray_1 = get_image_binarize(path_1)
        gray_2 = get_image_binarize(path_2)
        # Compare grayscale images between every 5th image and disparity map
        stereo = cv2.StereoBM_create(numDisparities=16, blockSize=9)
        # Save disparity map
        disparity = stereo.compute(gray_1,gray_2)
        disp_path = class_dir+str(count)+'.jpg'
        cv2.imwrite(disp_path, disparity)
        count = count + 1
```

DNN Model and CNN Model Code Snippet

```
class Conv2D(nn.Module):
    def __init__(self):
        super().__init__()
        self.network = nn.Sequential(

            nn.Conv2d(1,20,5),
            nn.ReLU(),
            nn.MaxPool2d(2,2),
            nn.Conv2d(20,64,5),
            nn.ReLU(),
            nn.MaxPool2d(4,4),
            nn.Conv2d(64,64,7),
            nn.ReLU(),
            nn.MaxPool2d(4,4),

            nn.Flatten(),
            #nn.Linear(3136,6000),
            #nn.ReLU(),
            nn.Linear(3136,1024),
            nn.ReLU(),
            nn.Linear(1024, 512),
            nn.ReLU(),
            nn.Linear(512,5)
        )
```

CNN Model Initialization

```
class LinearModel(nn.Module):
    def __init__(self):
        super().__init__()
        self.network = nn.Sequential(
            nn.Flatten(),
            nn.Linear(90000, 1024),
            nn.ReLU(),
            nn.Linear(1024, 512),
            nn.ReLU(),
            nn.Linear(512, 5)
        )

    def forward(self, x):
        return self.network(x)

model = LinearModel()
```

DNN Model Initialization

```
## Model Creation and Application
X_train, X_test, y_train, y_test = train_test_split(

# Use support vector classification
clf = SVC()
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
accuracy = accuracy_score(y_pred,y_test)
print("Prediction accuracy:",accuracy*100,"%")
```

SVC Model Initialization

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