CS6476: Computer Vision, Fall 2019
PS5

Instructor: Devi Parikh

Due **before**: Monday, November 25th, 11:58:59pm

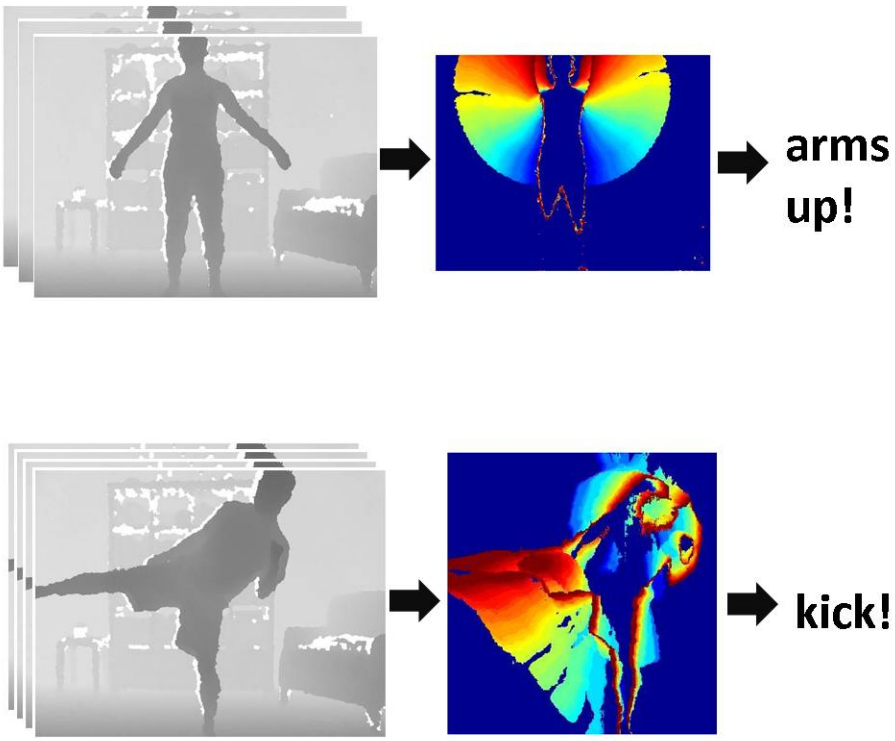
Instructions

1. Answer sheets, code and input/output images must be submitted on Canvas. Hard copies will not be accepted.
2. Please provide a pdf version of your answer sheet named: FirstName_LastName_PS5.pdf.
3. If your scripts are in Python, please use ".py" as file extension. If your scripts are in Matlab, please use ".mat" as file extension.
4. Please put all your code, input/output images and answer sheets in a folder (no subdirectories). Make sure your code is bug-free and works out of the box. Please be sure to submit all main and helper functions. Be sure to not include absolute paths. Points will be deducted if your code does not run out of the box.
5. If plots are required, you must include them in your answer sheet (pdf) and your code must display them when run. Points will be deducted for not following this protocol.
6. Your code and plots should use the same filenames mentioned in the question (if present). Variables in your code should use the same names that are mentioned in the question (if present).
7. Please make sure that the folder is named FirstName_LastName_PS5_mat if using Matlab and FirstName_LastName_PS5_py if using Python.
8. Zip the above folder and name the zipped file LastName_FirstName_PS5_mat.zip if using Matlab and LastName_FirstName_PS5_py.zip if using Python. Submit only the zip file.

1 Programming problem [100 points]

For this problem, you will implement an action recognition method using *Motion History Images*. Given a video sequence, the goal is to predict which of a set of actions the subject is performing. The basic idea is to use a sequence of depth images to segment out the foreground person, and then for each sequence, compute its motion history image (MHI). This MHI serves as a *temporal template* of the action performed, and can be further compressed into a set of 7 Hu moments. Once the Hu moments have been computed for all labelled training examples, we can categorize a novel test example by using nearest neighbour classification.

Video data You can access the video data here (unzipped data occupies about 530MB of disk space):
https://filebox.ece.vt.edu/~F15ECE5554ECE4984/resources/PS5_material/PS5_Data.zip
There are 5 directories within the zip file, each of which contains 4 sequences for one of the action categories. The 5 action categories are: *botharms*, *crouch*, *leftarmup*, *punch*, *righkick*. Each directory under any one of these 5 main directories contains the frames for a single sequence. For example, `punch/punch-p1-1/` contains one sequence of frames for *punch*.



The data are stored as `.pgm` images. Each pgm is a grayscale image, where the intensity is proportional to depth in the scene. Note that the image frames are named sequentially, so that if you use Matlab's `dir` command to gather all pgm's in a directory (or Python's `glob.glob` followed by `numpy.sort`) and then loop over the image list, they will be in the correct order. See the provided script `readingDataExample.m(py)` for an example of how to loop over the videos and read in the files.

Approach The main steps are as follows:

- Load the depth map pgms in a given sequence, and perform background subtraction to identify pixels on the foreground person. You should choose reasonable threshold(s) on depth based on examining an example or two. Global parameter settings should be sufficient for this data. Let's call the binary foreground silhouette difference images that you obtain here as $D(x, y, t)$.
- Use all difference images in a τ-frame sequence to compute its Motion History Image, H_τ:

$$H_\tau(x, y, t) = \begin{cases} \tau & \text{if } D(x, y, t) = 1 \\ \max\left(0, H_\tau(x, y, t-1) - 1\right) & \text{otherwise} \end{cases}$$

  where t varies from 1 to τ.
- Normalize the Motion History Image (MHI) by the maximum value within it.
- Use the MHI to compute a 7-dimensional vector containing the 7 Hu moments. This vector is the final representation for the entire video sequence, and describes the global *shape* of the temporal template in a translation- and rotation-invariant manner.

- Having computed a descriptor vector for each video sequence, evaluate the nearest neighbour classification accuracy using *leave-one-out cross-validation.* That is, let every instance serve as a *test* case in turn, and classify it using the remaining instances.
- For the nearest neighbour classifier, use the normalized Euclidean distance (i.e., where the distance per dimension is normalized according to the sample data's variance).
- Evaluate the results over all sequences based on the mean recognition rate per class and the confusion matrix.

See the paper *The Representation and Recognition of Action Using Temporal Templates by J. Davis and A. Bobick* for more background on computing the MHI (available here). For additional background on the properties of Hu moments, see *Visual Pattern Recognition by Moment Invariants by M. K. Hu* (available here).

What to implement, display and discuss in the writeup:

Write code for each of the following (along with any helper functions you find useful), and in your pdf write-up report on the results, briefly explain, and show images where appropriate. Your code must access the depth maps from sub-folders, named after each action, in your current working directory (*i.e* unzip the provided data in your current working directory).

1. **30 points**. Write a function `computeMHI.m(py)` that takes a directory name for a sequence, and returns the Motion History Image:

   ```
   function [H] = computeMHI(directoryName)
   ```

   In some other script (`generateAllMHIs.m(py)`), apply this function to compute Motion History Images for all the data, and display three examples from different action categories in a figure in the pdf, titled with the action category each one belongs to. (You will need to debug your background subtraction procedure to get this working.) Please submit the Motion History Images of all the sequences in a file called allMHIs.mat(npy). This file should contain a variable called `allMHIs` which is a matrix of size `MxNx20`.

2. **15 points**. Write a function `huMoments.m(py)` that takes a Motion History Image matrix and returns the 7-dimensional Hu moments vector:

   ```
   function [moments] = huMoments(H)
   ```

   Please submit the Hu moments vectors of all the sequences in a file called `huVectors.mat(npy)`. This file should contain a variable called `huVectors` which is a matrix of size `20x7`.

3. **20 pts**. Write a function `predictAction.m(py)` that predicts the label of a test sequence using nearest neighbour classification:

   ```
   function [predictedLabel] = predictAction(testMoments, trainMoments, trainLabels)
   ```

   where `predictedLabel` is an integer from 1 to 5 denoting the predicted action label, `testMoments` is a 7-dimensional Hu moment descriptor representing the test sequence, `trainMoments` is an Nx7 matrix of Hu moment descriptors for N training instances, and `trainLabels` is an Nx1 vector denoting the action category labels for all N training instances. Use the normalized Euclidean distance.

4. **20 points**. Write a script `showNearestMHIs.m(py)` that displays the top K most similar Motion History Images to an input test example, based on the normalized Euclidean distance between their associated Hu moment descriptors. (Note that you display MHIs but still refer to distance in terms of the videos' Hu moment vectors.) In the pdf writeup, display the results for two selected test examples (again, from different action categories), for K = 4.

5. **15 points**. Finally, write a script `classifyAllActions.m(py)` that performs *leave-one-out cross validation* on all the provided videos to determine the overall nearest neighbour recognition performance. This script should report the overall recognition rate, mean recognition rate per class, and display a 5 x 5 confusion matrix. In your write-up, discuss the performance and the most confused classes.

2 OPTIONAL: Extra credit (max 20 points)

1. Using ideas from any previous lectures, enhance the approach to try and improve the recognition results. For example, you might incorporate a different classifier, distance function, or descriptor. You might exploit the depth map for more than simply background subtraction, enhance the silhouette computation,... Explain clearly how you've extended the method, and report on the results. Explain in what ways things change relative to your implementation for Section 1, and why.

Deliverable checklist:

1. (Code) `computeMHI.m(py)` and `generateAllMHIs.m(py)`, (PDF) three titled/labelled examples from three different action categories, (Data) `allMHIs.mat(npy)`.
2. (Code) `huMoments.m(py)`, (Data) `huVectors.mat(npy)`
3. (Code) `predictAction.m(py)`
4. (Code) `showNearestMHIs.m(py)`, (PDF) Results for two test examples from different action categories for $K = 4$.
5. (Code) `classifyAllActions.m(py)`, (PDF) report and discuss results as mentioned in the question.

This assignment is adapted from PS5 of Kristen Grauman's CS 376: Computer Vision at UT Austin.