McGill University, Department of Electrical and Computer Engineering

Assignment 3: Safe Landing Zone

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1 Landing Zones

In this assignment you will implement an image processing algorithm that helps a drone to identify safe landing zones. Suppose the drone is equipped with a bottom facing camera that generates images like the ones shown in Figure .1.1. The algorithm must decide if: (1) the region is safe for landing (asphalt), Fig. 1.1(a); (2) is not ideal but can be used in an emergency (grass), Fig. 1.1(b); or (3) is completely inappropriate to be used as a landing zone (danger) Fig. 1.1(c). Figure 1.2 shows the block diagram of the proposed algorithm. First, the image is acquired. Then, a set of four features are extracted from the gray-level co-occurrence matrix (GLCM) associated with the acquired image. Next, the most relevant features are selected using a correlation-based selection algorithm. And finally, the classifier identifies one of the possible landing conditions.

(a) (b) (c)

Figure 1.1: Classes: (a) asphalt (safe); (b) grass (emergency); and (c) inappropriate (danger).

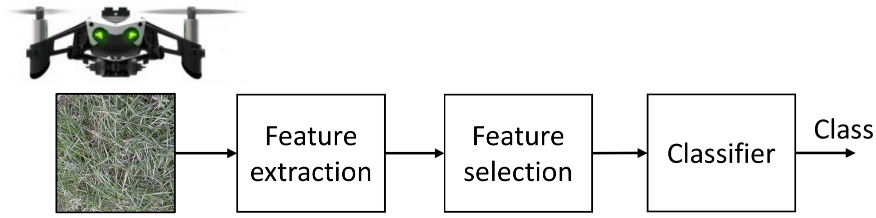

Figure 1.2: Block diagram o the proposed safe landing zone detection algorithm.

2 FEATURES EXTRACTION

Convert the RGB images to grayscale. Next, generate the gray-level co-occurrence matrix [1, 2, 3] (don't use a built-in function) and derive the statistics below (don't use a built-in function):

1. $Contrast$: Measures the local variations in the gray-level co-occurrence matrix.
2. $Correlation$: Measures the joint probability occurrence of the specified pixel pairs.
3. $Energy$: Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment.
4. $Homogeneity$: Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

These metrics provide information about the texture of an image and will be used as inputs to the classifier.

3 FEATURE SELECTION

The test set is composed by 150 images, 50 from each class: (a) safe; (b) emergency; and (c) danger.

Separate the samples of each class in two subsets with 25 images. One subset will be used to train your classifier, the other one will be used to evaluate its final performance. You are free to choose which classifier to use.

Assume that a good input feature vector contains features that are "highly correlated with the classification, yet uncorrelated to each other". Considering this premise, you will run a *feature selection* algorithm before training the classifier. You may use a built-in function to calculate the correlation between two random variables, but you must implement the rest of the *Feature Selection Algorithm* proposed by [4], Section 2.

After selecting the most relevant features, show plots for all possible feature pairs. All 3 classes must be represented on each plot. For instance, if after the selection phase, 3 features were selected (f_1, f_2 and f_3), then there will be 3 possible combinations, $f_1 \times f_2$, $f_1 \times f_3$ and $f_2 \times f_3$. You must generate 3 plots, one for each combination, and show the data for the 3 classes at the same plot.

4 Landing Zone Classification

In your experiments, consider two scenarios. In the first one, your classifier must be trained to identify one of three classes: safe, emergency ans danger. In this case, the performance of you system will be given by the *confusion matrix*. In the second scenario, your classifier must be trained to identify only two classes: safe (asphalt) or not safe (emergency and danger). In this case, the performance will be given by the *F-measure*.

References

[1] F. Albregtsen, *Statistical Texture Measures Computed from Gray Level Coocurrence Matrices*, November, 2008.

[2] L. K. Soh and C. Tsatsoulis, *Texture analysis of SAR sea ice imagery using gray level co-occurrence matrices*, IEEE Transactions on Geoscience and Remote Sensing, March, 1999.

[3] Robert M. Haralick, K. Shanmugam, and Its'Hak Dinstein *Textural Features for Image Classification*, IEEE Transactions on Systems, Man, and Cybernetics, November, 1973.

[4] Michal Haindl, Petr Somol, Dimitrios Ververidis and Constantine Kotropoulos *Feature Selection Based on Mutual Correlation*.