Getting started

The application is a combination of a .net/WPF GUI and a python commandline interface (CLI) which is called by the GUI. To run the application, extract the archive in which this report is contained, navigate to \Cbir\Cbir\bin\Debug\, and double-click the Cbir.exe executable. (Jump to <u>Potential errors</u>.)

Usage

To use the application, you will need to specify a query image and a set of features. The features determine how images are judged as "similar." In addition to the set of features, there is the option of using the relevance feedback (RF) algorithm. Relevance feedback allows you to mark result images as relevant and continue searching with the shared features (those shared between the query image and those marked relevant) taken into account.

Query image

To specify a query image, drag an image from windows explorer and drop it onto the main screen. (You will see a preview of the image in the query location as you drag it over the screen.)

Possible results folder

By default, when you choose a query image, its directory becomes the one searched for similar images. You can change the directory by dragging a folder from windows explorer and dropping it on the main screen. You will see the path of the folder displayed.

Example results and performance

Results for image 1.jpg

In the next few sections, you can see the results of a query using image 1.jpg (a picture of a landscape with green foreground, mountains in the middleground, and a blue sky with clouds). My similarity metric (used for determining precision - that is, "was this result valid?") was images having a blue sky with clouds (regardless of foreground). In retrospect, I can't say for certain whether that was a reasonable level of similarity to demand considering the features, but I suspect it was too much to expect.

In the screenshots with all texture features, you can compare the results to those of **contrast** alone to see that they match almost exactly. From the data, I confirmed my hypothesis that the high range

of values for contrast, even when Gauss-normalized in RF, overwhelm the other features (who have smaller ranges).

Energy







Contrast



All three texture features



RF with CC+TEX

This is relevance feedback with color code and all three texture features (energy, entropy, and contrast).

Iteration o





Iteration 2



Iteration 3



RF with CC+INT

This is relevance feedback with color code and intensity features.

Iteration o









RF with CC+INT+TEX

This is relevance feedback with color code, intensity, and texture.

Iteration o



Iteration 1



Iteration 2



Iteration 3



Precision for image 1.jpg

iteration ->	0	1	2	3
RF CC+TEX	5/20=0.25	6/20=0.3	8/20=0.4	5/20=0.25

iteration ->	0	1	2	3
RF CC+INT	6/20=0.3	6/20=0.3	8/20=0.4	8/20=0.4
RF CC+INT+TEX	4/20=0.2	6/20=0.3	8/20=0.4	4/20=0.2

Again, precision was based on how many images had a blue sky with clouds. It is unusual that the precision decreased on the 3rd iteration for two of the three RF combinations, and my only explanation is that my (fuzzy and imprecise) idea of relevance is only slightly correlated to the algorithm's idea of relevance.

Fitness for extension

For version 1 of the application, we were asked to implement only two features (color code and intensity histograms), with the user restricted to using one or the other, and there was no requirement for relevance feedback.

I won't say that it was easy to extend my application to include the new features (texture) or algorithm (relevance feedback), but it did not require me to discard much existing code. Since I had implemented part one's features using functions with a standard set of arguments, the three new texture features simply became similar functions. The distance function (which operated on each image's featureset) was able to stay essentially unchanged. The GUI, too, required only a little tweaking, although my implementation for tracking relevant images (across searches) made it more brittle and complicated.

I did make major changes in the core (python code), though, to reflect a better understanding of how new features could be added in the future. I hadn't taken the time to modularize part one, so I refactored most of the code and focused on creating multiple CLI levels for testing and debugging. For example, I now have a script to just extract the intensity histogram (normalized or not) from an image (specified as a path). This helped me focus the modularization efforts and also verify intermediate values.

In part one, I did quick-and-dirty (de)serialization of featuresets using python's pickle module. This method was brittle, because it relied on the structure of a class used in the code. In part two, I used an embedded sqlite database instead. (I had three tables, all indexed by image path, one each for intensity, color code, and texture features.) I could then easily view the values stored in the database, and now the database is responsible for handling concurrency (e.g. if I run multiple instances in parallel, which is possible, or if I want to do IPC via the DB rather than through console IO).

Current limitations

- You can unmark an image as relevant, but, if it was previously marked relevant and used in a search, it will actually remain relevant inside the program.
- Zoom is not implemented.

Future improvements

- Include a table (and, later, visualizations) of the intermediate values of featuresets
- Allow resizing of the query and result images
- Live-update and sort images as their distance values are computed
- Run images through core code in parallel

Potential errors

Python files not in same folder as .net executable

Please verify that the python files are in the same folder as Cbir.exe.

Python and/or libraries not installed

Install python 2.7 and the following libraries:

- numpy
- docopt