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Colour Correlation Window Matching Using Colour Spaces

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Abstract

Consider two small rectangular windows, each of which is centered at a different pixel in two different color images. Correlation is the process of computing the similarity between these two windows. If the camera rotation between the two images is not large then if these two pixels represent the same physical surface point then the similarity, and hence the correlation value, should be high. While correlation is a well known technique in computer vision, there are many possible variations. The main variability comes in the type of correlation algorithm, the colour space that is used, and the size of the window. This paper describes a set of experiments whose goal is to explore the impact of changing these three parameters. The methodology is first to manually select a set of matching features between two images, which are known as the ground truth. Then the different correlation variations are compared in terms of their ability to determine the correct matching feature out of all the possibilities.

1 Introduction

A well known problem in computer vision is the matching of features between two images. Features may represent corners or edges in the image, and the most common method to match these features is correlation. The correlation function returns the similarity between the feature points of two different images. It has as input two small rectangular windows that are centered on these feature points in both images.

There are a number of different correlation algorithms: Least Squares, Cross-correlation, Histogram, Ordinal Measures and an Accumulated Differences. It is also possible to perform the correlation on different color spaces, and the possibilities are the RGB, HSV, HLS and CIE colour spaces. Finally, there is also variability in the Correlation Window size.

With all these variations a number questions can be asked:

- Is there a "best" Correlation Method.
- What effect do the various colour spaces have on the Correlation Methods.
- How do the Correlation Methods behave when changing the Correlation Window size.

The goal of this paper is to present an experimental methodology and a set of experiments which attempt to answer these questions.

2 Correlation Window Methods

First we describe the different types of correlation methods that are in common usage. A correlation window is a predefined $n \times n$ area around a single point. Usually n is a positive odd integer in the range of three to twenty [3]. The total number of pixels in the correlation window is N, which is equal to $n \times n$.

The correlation methods we have implemented are the Least Squares, Histogram, Bhat and Nayar's Ordinal Measure [5], Normalized Cross-Correlation, as well as the Accumulated Differences approaches.

In all these cases the input to the correlation functions are the two windows I_1 and I_2 and the output is value between zero and one, where zero is a perfect match, and one is a perfect mismatch. More formally the correlation function is defined as $\varphi(I_1, I_2) \in [0, 1]$. We also assume that the image pixels of the two images are bounded, that is $I_1(I), I_2(I) \in [0, k]$, where k is typically a small integer. In this notation the index I ranges over each of the N pixels in the correlation window.

We now describe each of the implemented correlation methods in more detail.

2.1 The Least Squares Method

The Least Squares Method computes the similarity between the two windows by simply computing the sum of squares difference between the pixels.

$$\varphi = \frac{\sum_{i=1}^{N} (I_1(i) - I_2(i))^2}{k^2 \cdot N} \qquad (1)$$

2.2 The Histogram Method

The Histogram Method first places the pixels in the correlation windows I_1 and I_2 into j equally distributed bins, where each bin contains the number of pixels that are in the range of that bin. More formally, if a pixel p $\in [0, k]$, then each bin has a range of k/j consecutive pixels. The first of j bins counts the number of pixels which have values from zero to $k/j-1$, the second from k/j to $2(k/j)-1$ and so on. This is knows as a histogram, and j defines the granularity of the histogram. The histogram values are then compared to each other using the sum of the differences per bin:

$$\varphi = \frac{\sum_{i=1}^{j} |H_1(i) - H_2(i)|}{2 \cdot N} \qquad (2)$$

2.3 The Ordinal Measures

Ordinal Measures are based on relative ordering of values in an image window. The relative ordering of image values in each window is represented by a rank permutation, which is obtained by sorting the image values. Since the rank permutations are invariant to monotone transformations of the image values, the coefficients are unaffected by nonlinear effects like gamma variations between images [5].

2.4 The Normalized Cross Correlation

The Normalized Cross-Correlation of an image I_1 and I_2 having N data points is given by:

$$\varphi = \frac{\sum_{i=1}^{N} (I_1(i) - \overline{I_1}) \cdot (I_2(i) - \overline{I_2})}{2N \cdot \sqrt{\sigma(I_1) \cdot \sigma(I_2)}} \quad (3)$$

Here $\overline{I_1} = (\sum_{i=1}^{N} I_1(i))/N$ is the the average pixel values in the first window and $\overline{I_2}$ is defined similarly. Also, $\sigma(I_1) = \sqrt{\sum_{i=1}^{N} (I_1(i))^2 - (\overline{I_1})^2}$ is the standard deviation of the first image in the window, and $\sigma(I_2)$ is defined similarly.

This advantage of this approach over the least squares method is the ability to deal with an additive transformation brought on for example, by a global change in the lighting.

2.5 The Accumulated Differences Correlation

The Accumulated Differences is another Correlating Window method for image sub- regions given by:

$$\varphi = \frac{\sum_{i=1}^{N} |I_1(i) - I_2(i)|}{k \cdot N} \quad (4)$$

3 Colour Spaces

A colour space is a specification of a 3D colour coordinate system and a visible subset in the coordinate system within which all colours in a particular colour gamut lie [4]. There are a number of different colour spaces used in practice.

3.1 RGB (Red, Green, Blue)

The RGB (Red, Green, and Blue) colour space is the unit cube subset of the 3D Cartesian coordinate system. The individual contributions of each primary colour are added together to yield the RGB Colour Model [4].

3.2 HSV (Hue, Saturation, Value)

The HSV (Hue, Saturation, and Value) colour space is user-oriented because it is based on representing colour intuitively using tint, shade, and tone.

3.3 CIE (Commission Internationale de l'Eclarirage's)

The CIE (Commission Internationale de l'Eclarirage's) proposes a colour scheme based on the perceptual uniform colour system (UCS). The conversion from RGB to CIE's XYZ colour system occurs through the linear transformation as follows:

$$x = \frac{X}{X+Y+Z}, y = \frac{Y}{X+Y+Z} \quad (5)$$

where

$$X = 0.619R + 0.177G + 0.204B \quad (6)$$
$$Y = 0.299R + 0.586G + 0.115B \quad (7)$$
$$Z = 0.56G + 0.944B \quad (8)$$

3.4 Other Colour Spaces

The normalized TSL (Tint, Saturation, and Luminance) chrominance-luminance space, CMY (Cyan, Magenta, and Yellow), and the YIQ (U.S. colour broadcast TV format) are other common colour spaces.

4 Correlation Testing

To test the various correlation methods (Least Squares, Cross-correlation, Histogram, Ordinal Measures and an Accumulated Difference method) as well as test the impact of using different colour models (RGB, HSV, HLS, and CIE) we use the following method.

1. Select pairs images (I_1 and I_2) that have a sufficient overlap [2]. We assume that the overlap is at least 70 % of the image size.

2. Find corresponding feature points in each image (f_1 and f_2) [3]. These feature points are the ground truth, they are known to be correct.

We perform the testing by trying each permutation of correlation method and colour matching using the given image pairs and features. We correlate every feature combination, which is a total of (f_1 x f_2) possibilities. Only one of these is the correct match, and the correlation succeeds only if we find the correctly matching features pair out of the (f_1 x f_2) possibilities.

5 Experimental Results

In Figure 1 are two images, each of size 768 x 512 that we use in the experiments. Each image has a white box at the predefined features. The correspdonence between the features (that is which of the crosses match) is selected by hand, and is the ground truth. We have used three pairs of images to perform the experiments.

Figure 1: Two images which have 127 matching features selected by hand.

The results of the comparisons of the various correlating window methods are depicted in Table 1.

This table shows that out of all the correlation methods the Cross-correlation method seems to produce the best results in terms of finding the correct match.

The next experiment evaluates the impact of using components of the colour spaces instead of using the entire colour

Method	**RGB (%)**	**HSV (%)**	**HLS (%)**	**CIE (%)**
Least Squares	70.8	52.0	0.8	66.9
Histogram	15.7	18.9	2.4	9.5
Ordinal Measure	39.4	22.0	8.7	40.9
Norm. Cross-corr	78.0	61.4	0.8	78.0
Accum. Differences	70.1	54.3	7.1	64.6

Table 1: Comparisons of Correlating Window Methods (9 x 9) with various Colour Spaces given in the percentage of correct correlation's.

space. For example, is it feasible to use only one component, say the Hue, of the HSV colour space to acquire adequate results? The answer is tabulated in table 2. The experiment was run on image set 3 having size 768 x 512 using a 9 x 9 pixel correlation window. The cross-correlation method was used in the tabulation of Table 2.

From table 1 we know that the 'best' correlation was 78%. In table 2 we see that the individual RGB components range from 75.6 to 77.2 %. Also the HSV Value component gave good results. The CIE components faired similarly to the RGB components, not surprising since CIE is a linear combination of RGB.

This last experiment compares Correlation Window methods to Correlation Window sizes using the RGB Colour Space. One would expect that the larger the Correlation Window size, the more accurate the matching. This is indeed the case, as can be seen from table 3.

Figure 3 is the graphical interpretation of table 3. The Least Squares and the Accumulated Differences method have the highest number of correct correlation's using the RGB colour space; image set 3 with 175 correlation points. The Normalized Cross-Correlation Method does not do well for small Correlation Windows but gives better results when the correlation window size is high.

6 Conclusions

This paper has presented an evaluation of different correlation windows and different colour spaces. The correlation methods that were tested are the Least Squares, Cross- correlation, Histogram, Ordinal Measures, and Accumulated Differences. The colour spaces tested were RGB, HSV, HLS, and CIE. We have also performed these tests with different window sizes (3x3, 5x5, 7x7 etc.) as well as with different image sets. The image sets can have several interesting differences such as translations, rotations, different overlap configurations, any number of correlation points, and combinations of these.

The testing consisted of comparing Correlating Window Methods with various Colour Spaces, image sets with individual Colour Components, and Correlation Window methods with Correlation Window sizes. Since the ground truth in terms of correct matches was known a-priori we were able to test how well each permutation faired in terms of finding the correct matches.

The Normalized Cross-Correlation method faired well for a 'small' number of correlating points using a large Correlation Window size. The Least Squares and Accumulated Differences method performed well over all. The Histogram method performed poorly for small Correlation Window sizes but performed better

Image Set	**PTS**	**R** (%)	**G** (%)	**B** (%)	**H** (%)	**S** (%)	**V** (%)	**C** (%)	**I** (%)	**E** (%)
1	127	77.2	75.6	76.4	11.8	52.0	74.8	77.2	75.6	74.8
2	319	49.5	48.9	48.6	8.8	35.1	49.5	48.9	49.2	48.6
3	175	76.0	77.1	77.7	13.7	54.3	77.7	76.6	78.3	78.3

Table 2: Comparisons of Correlating Window Methods (9 x 9) with various Colour Spaces given in the percentage of correct correlation's.

Correlation Window Method	**3x3** (%)	**5x5** (%)	**7x7** (%)	**9x9** (%)	**11x11** (%)	**13x13** (%)	**15x15** (%)
Least Squares	52.0	70.9	81.1	89.7	92.6	94.3	94.3
Histogram	14.3	13.7	23.4	29.1	38.9	44.0	52.6
Ordinal Measure	8.6	33.1	54.9	60.0	63.4	61.1	54.3
Norm. Cross-corr	22.9	53.7	68.0	78.3	82.9	86.3	89.1
Accum. Differences	49.1	71.4	83.4	91.4	92.6	94.3	90.9

Table 3: Correlation Window methods compared to Correlation Window sizes using the RGB Colour Space. The result is given in percentage of a correct match across 175 Correlation Windows of image set 3.

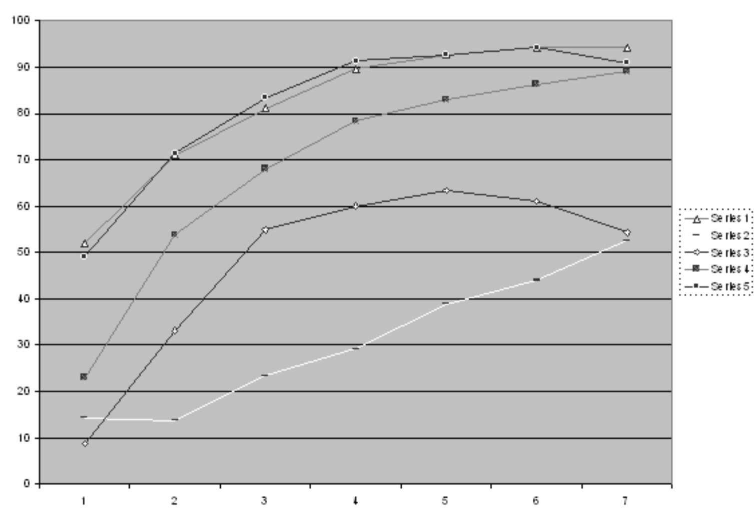

Figure 2: Correlation Window methods compared to Correlation Window sizes using the RGB Colour Space from data of table 3. Series 1 = Least Squares, Series 2 = Histogram, Series 3 = Ordinal Measures, Series 4 = Normalized Cross-Correlation, Series 5 = Accumulated Differences.

as the Correlation Window size increased.

The RGB and CIE colour space performed well overall, their similar performance can be attributed to the fact that they are linear combinations of each other. The HSV colour space performed poorly overall but the Value component on its own performed very well. The Value component compiled results favorable to that of the combined RGB colour space. Improvements to the model can be made here since the combination of the various colour space components was ignored. It may be possible to combine various components across colour spaces in such a way that they will improve the resulting correlation.

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