Comparing two images

Method proposed by Marsha-Jo Hannah

1 Feature Selection

The first step in our matching process is to select a set of well-scattered windows in one image, such that each window contains sufficient information to produce a reliable match. To accomplish this, a statistical operator $Interest$ is passed over the image; this is a product of the image variance and the minimum of ratios of directed differences (hence edge strength) over windows of the specified size, i.e.

$$Interest(x,y) = Var(I,x,y) * \min\left(\frac{Dif_1(x,y)}{Dif_2(x,y)}, \frac{Dif_2(x,y)}{Dif_1(x,y)}, \frac{Dif_3(x,y)}{Dif_4(x,y)}, \frac{Dif_4(x,y)}{Dif_3(x,y)}\right)$$

where

$$Var(I,x,y) = \frac{1}{n}\sum_{dx=-wx}^{wx}\sum_{dy=-wy}^{wy}(I(x+dx,y+dy) - \overline{I}(x,y))^2$$

$$\overline{I}(x,y) = Mean(I,x,y) = \frac{1}{n}\sum_{dx=-wx}^{wx}\sum_{dy=-wy}^{wy} I(x+dx,y+dy)$$

$$Dif_1(x,y) = \frac{1}{n}\sum_{dx=-wx}^{wx}\sum_{dy=-wy}^{wy}(I(x+dx,y+dy) - I(x+dx+1,y+dy))^2$$

$$Dif_2(x,y) = \frac{1}{n}\sum_{dx=-wx}^{wx}\sum_{dy=-wy}^{wy}(I(x+dx,y+dy) - I(x+dx,y+dy+1))^2$$

$$Dif_3(x,y) = \frac{1}{n}\sum_{dx=-wx}^{wx}\sum_{dy=-wy}^{wy}(I(x+dx,y+dy) - I(x+dx+1,y+dy+1))^2$$

$$Dif_4(x,y) = \frac{1}{n}\sum_{dx=-wx}^{wx}\sum_{dy=-wy}^{wy}(I(x+dx+1,y+dy) - I(x+dx,y+dy+1))^2$$

Local peaks in the output of this operator are recorded as the preferred places to attempt the matching process. The motivation behind this operator is that it penalizes windows with low information and windows whose only information is contained in strongly linear edges, as both of these situations cause difficulties in obtaining the correct match via area-based correlation. The chosen windows are characterized by their center points, which are referred to as "interesting points" [Moravec, 1980]. To ensure that the selected windows are well-scattered in the image, the image is divided into a grid of subimages, and the relative ranks of the interesting points within their grid cell are recorded; this permits the most interesting point(s) in each area to be matched first.

Note that our "features" are selected in only one image, to be matched by a statistical technique based solely on image intensities. Therefore, the fact that our feature detector is not invariant with respect to differences between images is irrelevant to our technique.

2 Similarity Measure

Whether or not point (x_1, y_1) in image I_1 is matched by point (x_2, y_2) in image I_2 is determined by computing a variation of the normalized cross-correlation $Corr$ over windows surrounding the points.

$$Corr(x_1, y_1, x_2, y_2) = \frac{|Covar(I_1, x_1, y_1; I_2, x_2, y_2)| * Covar(I_1, x_1, y_1; I_2, x_2, y_2)}{Var(I_1, x_1, y_1) * Var(I_2, x_2, y_2)}$$

where

$$Covar(I, x, y; J, u, v) = \frac{1}{n} \sum_{dx,dy} (I(x+dx, y+dy) - \overline{I}(x, y)) * (J(u+dx, v+dy) - \overline{J}(u, v))$$

The matching point is taken to be the point in I_2 with highest correlation, as located by one of a variety of search algorithms. Note that we are using the square of what is ordinarily defined as normalized cross-correlation, except that the sign of the numerator has been preserved. Also, all sums exclude any pixel pair with $I_1(x_1, y1) = 0$ or $I_2(x_2, y2) = 0$, which is our "marker" for invalid data. Boundary conditions are handled as if the images were surrounded in infinite fields of 0's.

Normalized cross-correlation is invariant to linear radiometric changes (i.e. intensity changes of the form $I_2(x_2, y_2) = aI_1(x_1, y_1) + b$) between images. Because we use small windows (typical window radii are $wx = wy = 5$), minor geometric changes (such as scale changes less than 20% or rotations of less than 11.3^o) do not affect the result; larger distortions degrade the correlation, which may cause matching to fail.