Flow Estimation Using More Information

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(This work has been developed further and published in Artificial Intelligence [3].
The further development of this work is also the subject of a patent application [1])

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Abstract

Most existing pixel-based optic flow methods work on the principle of finding an optimal value for the optic flow at each pixel and then reducing errors and ambiguities by some sort of smoothing of the resulting vector field. A weakness with these approaches is that no information about possible original flow vectors (other than the "optimal" one) is considered; thus much potentially useful information is lost. In this report a new approach is described, which keeps information about all the possible flow vectors at each pixel for use *during* the smoothing (error correction) stage, resulting in better flow estimation.

Keywords: Optic flow, 2D motion estimation, correlation

1 Introduction and Review

Most existing pixel-based optic flow methods work on the principle of finding an optimal value for the optic flow at each pixel and then reducing errors by some sort of smoothing of the resulting vector field. These errors arise largely because of two factors. The first of these is flow measurement inaccuracy, arising from the various noise processes which occur throughout the image capturing and digitization, along with non-modelled changes in the scene being digitized. The second cause of "error" is the well known aperture effect [5] where, for example, flow can only be estimated perpendicular to an edge, and the flow component parallel to the edge must be inferred from measurements elsewhere.

Various methods of overcoming these problems have been suggested. 2D-feature-based optic flow methods (e.g., [8, 9]) overcome the aperture problem by only calculating flow at places in the image where the 2D flow field is well conditioned. 1D-feature-based (edge-based) methods (e.g., [4, 2]) find optic flow at edges, and interpolate around contours to enable estimation of the flow component parallel to the edges. However, none of these methods carry out very much error suppression on the flow estimates. The simplest gradient-based methods (e.g., [5]) reduce flow error by effectively applying linear smoothing to the flow field, whilst more advanced methods (e.g., [6, 7]) apply anisotropic smoothing, and try not to smooth flow across image edges or motion boundaries.

A serious weakness with these approaches is that no information related to possible alternatives to the "optimal" original flow vector is used; much potentially useful information is lost. In other words, the initial flow vector field is created with only a single vector estimated at each image point. There is no reason why a richer information field could not be produced, that stored, for example, all possible flow vectors at each image position, along with their initial relative "probabilities". These probabilities could be derived from any particular flow estimation method already in use, e.g., patch correlation.

In this report a new approach is described. ISIS - Integrated Support Information Spreading - keeps the early flow information for use *during* the smoothing/error correction stage, thus using more of the available information and resulting in better flow estimation.

Since the original idea for ISIS was developed, further work has been carried out to improve the error correction method, by Hayton, Brady and Smith [3]. Therefore this report is kept brief, as an introduction to the basic concept of using all of the flow information for as long as possible.

2 ISIS – Details

ISIS operates on a pair of images, attempting to provide a good estimate of optic flow, i.e., the motion field that transforms the first image to the second. This new approach to optic flow estimation is described in this section.

Firstly, a basic method of finding optic flow is decided upon. A simple and intuitive method is cross-correlation, where a patch centred on a point in the first image is moved around the corresponding point in the second image. For an example image pair, see Figure 1. For each point in the first image, a corresponding

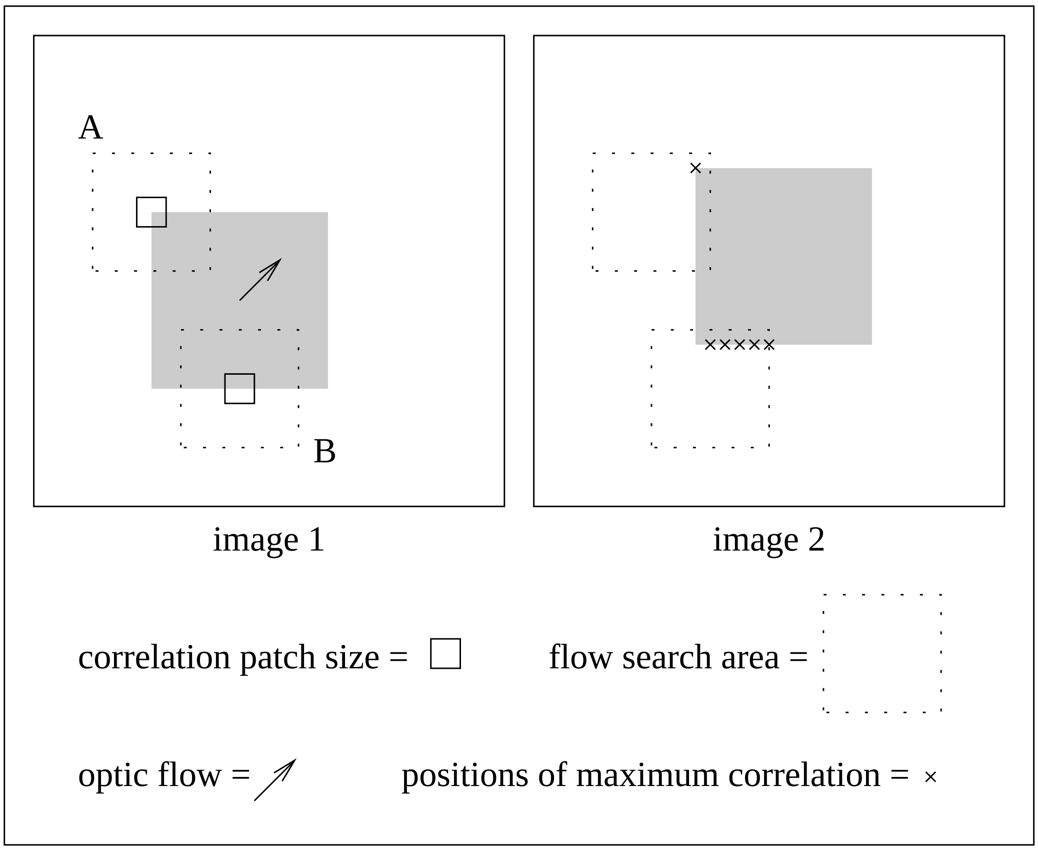

Figure 1: Example pair of images with optimal optic flow values shown for two example image positions. Position A has an unambiguous optic flow vector, whilst position B could move to one of several points on the bottom edge of the grey square.

2D array of optic flow scores is derived - currently, an array of cross-correlation scores. The size of the array is limited by the maximum allowed optic flow. Previously, researchers have only been interested in taking the maximum value from within this array, giving an immediate single estimate of the optic flow. Score arrays corresponding to the example starting positions A and B from Figure 1 are shown in Figure 2.

$$\begin{pmatrix} 30 & 30 & 30 & 30 & 30 & 35 & 45 & 50 & 45 \\ 30 & 30 & 30 & 30 & 30 & 40 & 50 & 100 & 50 \\ 30 & 30 & 30 & 30 & 30 & 35 & 45 & 50 & 45 \\ 30 & 30 & 30 & 30 & 30 & 30 & 30 & 30 & 30 \\ 30 & 30 & 30 & 30 & 30 & 30 & 30 & 30 & 20 \\ 30 & 30 & 30 & 30 & 30 & 30 & 30 & 30 & 20 \\ 30 & 30 & 30 & 30 & 30 & 30 & 30 & 30 & 20 \\ 30 & 30 & 30 & 30 & 30 & 30 & 30 & 30 & 20 \\ 30 & 30 & 30 & 30 & 30 & 30 & 30 & 30 & 20 \end{pmatrix}$$

A

optic flow corresponding to maximum score is (3,3)

$$\begin{pmatrix} 40 & 50 & 60 & 70 & 80 & 80 & 80 & 80 & 80 \\ 40 & 50 & 65 & 75 & 100 & 100 & 100 & 100 & 100 \\ 40 & 50 & 60 & 70 & 85 & 85 & 85 & 85 & 85 \\ 40 & 45 & 55 & 60 & 70 & 70 & 70 & 70 & 70 \\ 40 & 43 & 45 & 50 & 55 & 55 & 55 & 55 & 55 \\ 40 & 40 & 40 & 40 & 40 & 40 & 40 & 40 & 40 \\ 40 & 40 & 40 & 40 & 40 & 40 & 40 & 40 & 40 \\ 40 & 40 & 40 & 40 & 40 & 40 & 40 & 40 & 40 \\ 40 & 40 & 40 & 40 & 40 & 40 & 40 & 40 & 40 \end{pmatrix}$$

B

optic flows corresponding to maximum scores are (0,3), (1,3), (2,3), (3,3), (4,3)

Figure 2: Example flow score arrays corresponding to positions A and B in Figure 1.

The problem, in the case of position B in these example images, is that there is no unambiguous “best” optic flow vector. This will be even more strongly the case in “flat” regions, with no strong edges or texture. Although, in real images, there will probably be a single correlation score which is greater than all the others, it will not be very much greater (except at corners, e.g., position A, or perhaps in highly textured areas), and thus treating this vector as *the optic flow vector* is throwing away data which describes which other possible optic flow vectors are nearly as good, and which may be more valid, once the local neighbourhood is taken into account.

The resulting grid of 2D arrays of optic flow scores is processed so that the 2D arrays interact with each other on a local level. A “smoothing” filter is applied to combine local arrays, so that noise in the flow estimation is reduced, and flow ambiguities are resolved. Thus each array is combined with its local neighbours using an appropriate filter, to produce an updated version of the array. This is carried out for each array, and the whole process is iterated many times, allowing information to spread around the array grid.

Various filters, used to combine information from local 2D arrays, have been tried. The most successful filter effectively insists that for an array element to stay high after filtering, the corresponding element must be high in all local arrays. A simple way of producing this "logical anding" effect is to multiply all the corresponding elements together (and take the nth root, so that iterations of this procedure do not overflow numerically). Thus, for each element $S^{(x,y)}(i,j)$ at position (i,j) in the array associated with image position (x,y), with a local array neighbourhood $(x',y') \in l$ of n_l arrays, the new value for S after filtering is:

$$S_{new}^{(x,y)}(i,j) = \sqrt[n_l]{\prod_l S_{old}^{(x',y')}(i,j)} \tag{1}$$

Once the 2D flow arrays have been optimally filtered (typically, ten iterations), the position of the maximum within each array is taken to be the optic flow at that point in the image. (There is obviously scope here for trivially finding sub-pixel flow accuracy using interpolation within the array.)

In Figure 3 an example is given of finding optic flow between two MRI images of a subject's brain. The two images were taken two years apart and do not correspond to exactly the same slice of the brain. The six images show the estimated (maximal score) optic flow at various iterations of the error correction filter. At zero iterations, there is a large amount of noise in the flow field. After the ninth iteration a smooth flow field is obtained.

References

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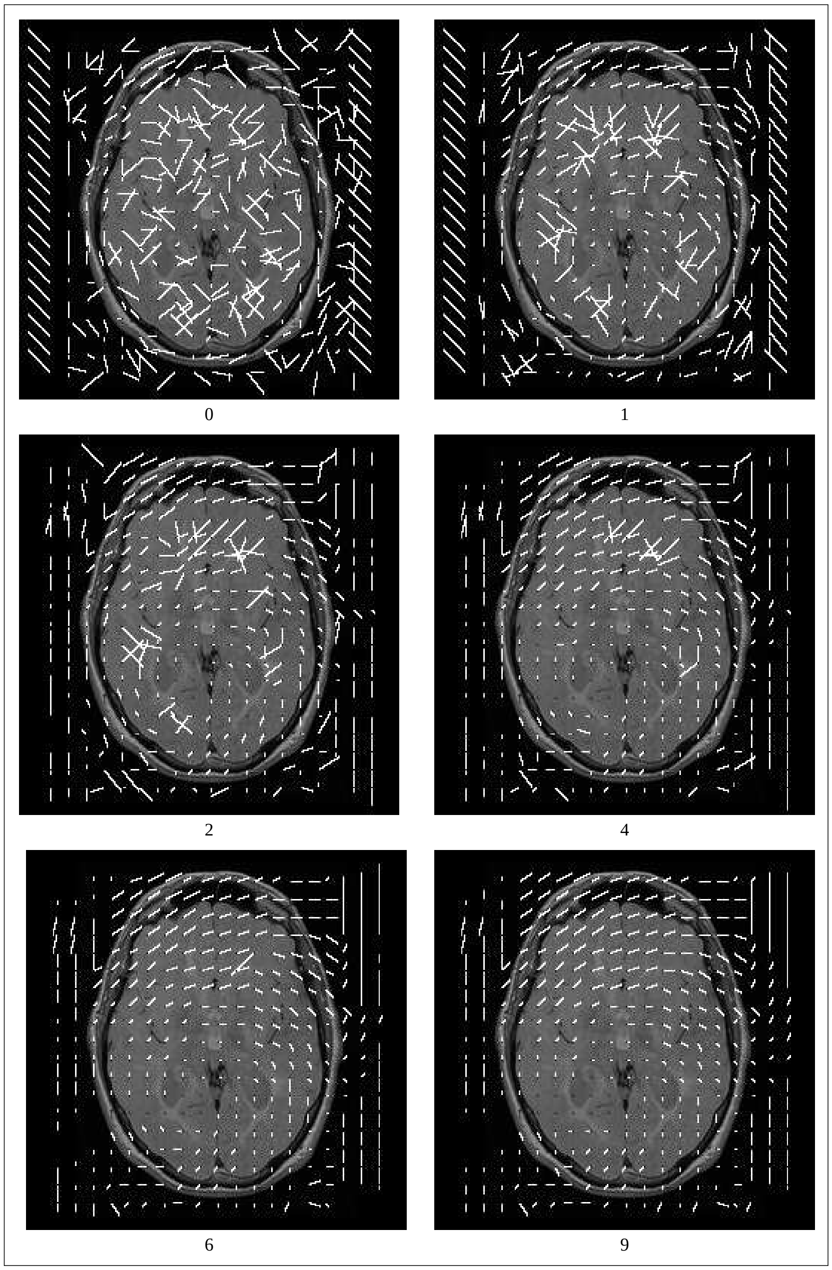

Figure 3: Example results from a pair of images of a brain, showing different iteration levels of the error correction filter.

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