A short survey of the potential of SHV for fingerprint analysis.

I have been aware of scientific research into the possibilities of automatic fingerprint analysis going on for at least the last 30 years - since a major push in that direction back in the 1970's, when then colleagues of mine at B.Ae. were exploring the possibilities of the developing potential of coherent optical correlation using the (then new) laser technology. At about the same time I was starting my own attempts to produce a simulation of the powerful capabilities of human vision for subtle recognition.

Over the intervening years my main interests were diverted to a number of more general properties and capabilities of human vision, from which it has been possible to produce a software simulation of the early stages which matches known (experimentally determined) thresholds (limitations) in many ways and, as spin-offs, has shown possible ways of explaining (and simulating) a number of higher order obvious functions of vision. The main software (SHV) has been operating as a Windows friendly package now for some time, this software having major capabilities, in addition to several others, of sensing local brightness & colour discontinuities in an image at a single pixel level to better than 0.1 pixels in radial position and better than 1 degree in local edge orientation (see Ref. 1, Chapter 4). From these raw local data, supplementary software has been developed which can analyse mismatches in image 'pattern' in both 2D linear space and rotational space (Ref. 1, Chapter 9.9.3; Ref. 2) plus, in addition, can generate 2D edge maps of local edge curvature (Ref. 1, Chapter 12).

Then, some two years ago, as part of my investigations as to whether, in the intervening years, others had developed similar methods of simulating these and other (often quite remarkable) capabilities of human vision, as compared with the more obvious capabilites of conventional image processing methods, I came across an example of what could be achieved in terms of fingerprint analysis utilising the image processing facilities contained as part of a mathematical package associated with MathCAD. I was disturbed to find that, at least as far as that commercial package was concerned, the best that could be achieved was the sensing of individual pixels laying on a brightness discontinuity (edge) in an image, with little additional information being readily extractable (figures 1 & 2).

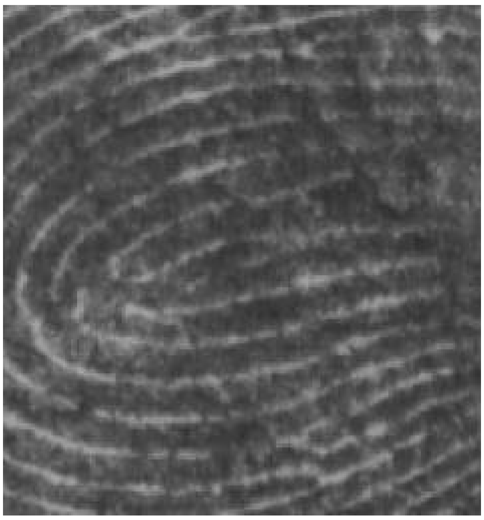

Fig. 1. Typical fingerprint.

Fig. 2. Edge map from MathCAD ('Canny' operator).

I was prompted at the time, as part of a more general comparison exercise, to carry out some limited comparative processing using the edge analysis facilities contained in MathCAD and those contained in SHV (Ref. 3). Figure 3 shows the equivalent results to figure 2 when figure 1 is processed through SHV and presented at single pixel resolution. The substantially similar results should be evident. However, in order to demonstrate the greatly increased resolution and orientation data also contained in the SHV output, it is necessary to present the output data from SHV at a greatly increased scale. To facilitate pictorial presentation of this, firstly figure 4 shows a cropped portion of the output from figure 3 (left of centre) plotted at a substantially increased scale. Then figure 5 shows the same portion of the fingerprint edge map obtained from SHV, but this time plotted at a scale of X10 , with the individual edge fragments detected shown as 'dipoles' indicating both the sub-pixel position and local edge orientation.

Fig. 3. SHV single pixel edge map.

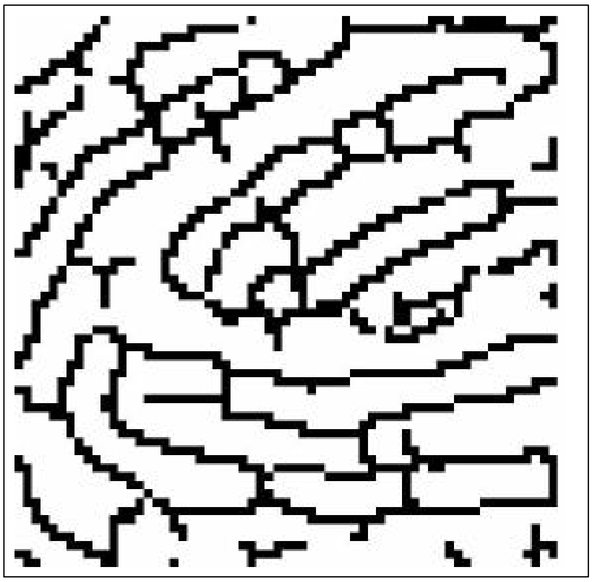

Fig. 4. Magnified view of cropped portion of figure 3.

It is only owing to the 'trigger' provided by the recent major UK government push towards widespread biometric testing / checking by means of fingerprints and other biometric measures that I have considered a need to look again at what I might be able to offer from my (now essentially complete) simulation of early human vision (as embodied in SHV). What I seem to find, having had this new look at the potential, is that, within SHV and its supplementary analysis processes, there is great potential for automatic fingerprint categorisation & comparison which can be based on very simple digital imaging and analysis. At this point I hasten to add that I have no idea as to how currently proposed methods for biometric testing are supposed to work, but I am suspecting (from knowledge of other loosely related optical imaging tasks) that any such methods will be based on considerably more expensive (and complex) equipment & techniques related to 2D cross-correlation.

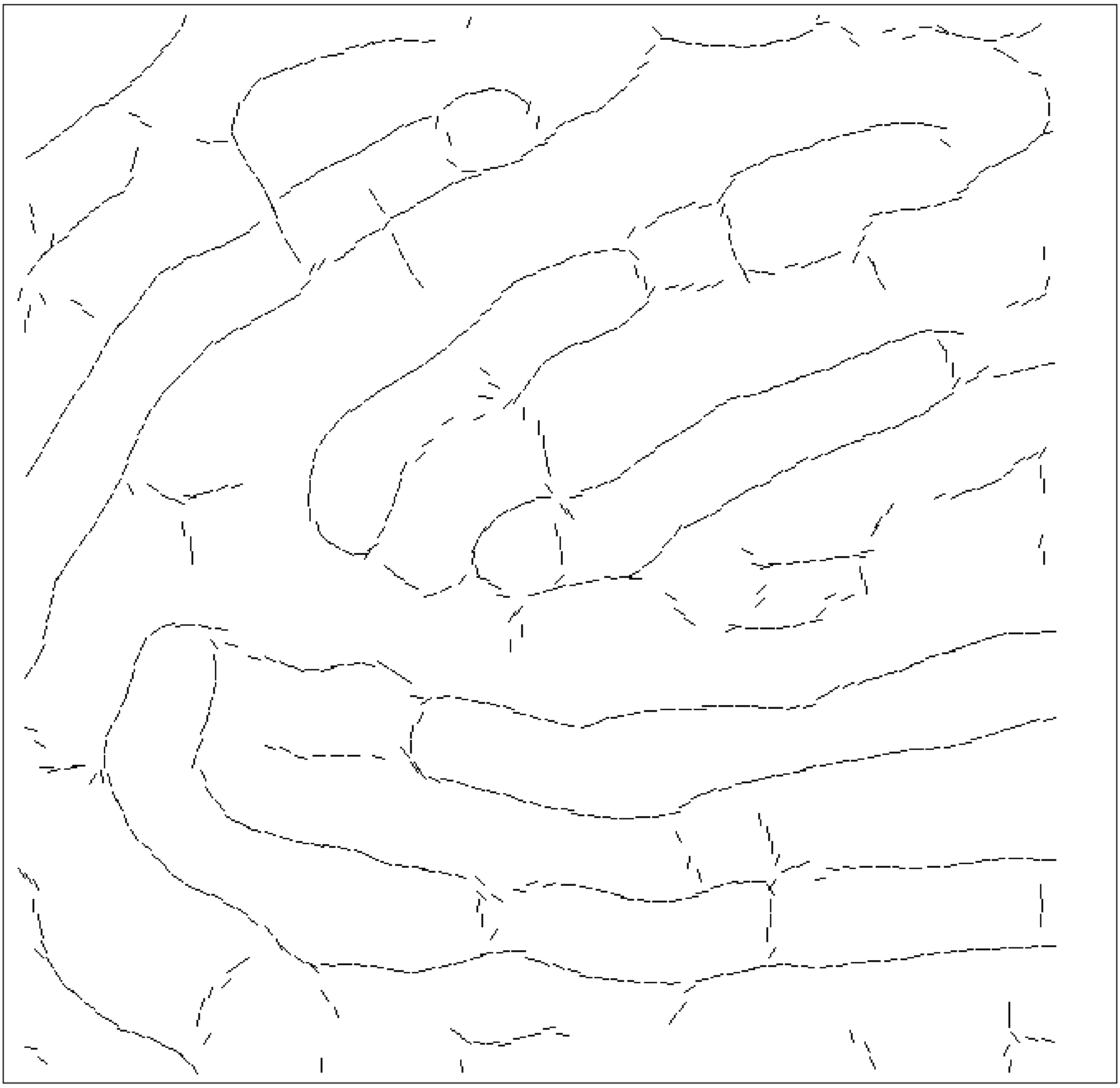

Fig. 5. 0.1 pixel resolution plot of the SHV output data as shown at single pixel level in Fig.4.

This short report is, therefore, an attempt to present a summary of what I perceive to be the main factors on which fingerprint recognition is dependant, together with what the SHV approach has to offer as an alternative to cross-correlation.

Possible factors related to fingerprint comparison & recognition.

As I see it, the following are the main attributes which it is necessary to sense (recognise) and compare for reliable fingerprint recognition / comparison.

- The detection of all (or at least the majority of) 'valleys' or valley edges in a typical fingerprint.
- The recognition of various lines, whorls & other features in the 'valley' or edge map.
- The accurate measurement of the characteristics of the local features.

- A ready means of accurate comparison of the measurements of a pair of fingerprint maps, in particular including a means of automatic registration of the pair of images.

On the face of it, these requirements might not sound too onorous. However, let us look at the requirements in more detail.

Detection of local edges of 'valleys' (to the nearest pixel) - i.e. the classical edge detection problem - is rather straight-forward. In fact, I would expect that, in any two samples obtained of the ***same*** fingerprint, such variations as pressure and possible smear in capturing the print should mean that excessive accuracy of local position measurement is unwarranted (and unnecessary?).

However, when it comes to the ***recognition*** of local 'features' such as whorls, what seems to be vastly more important than simple edge ***detection*** is an ability to measure the local ***orientation & curvature*** of the valley edges. In conventional image analysis such measures as these are normally only derived by substantial secondary analysis working over substantial extents of edges (and can therefore only be of low spatial resolution.

In automatic comparison of a pair of edge maps, not only is it necessary to determine these second order local characteristics of the edge maps ***individually***; it is also necessary to be in a position to overlay the two maps accurately in both 2D space and mean orientation.

I am well aware that it has been claimed for many years that the best way to tackle this sort of problem is by use of auto & cross correlation (i.e. in 2D spatial frequency space after Fourier transformation). However, I have always had serious reservations about the practicality of such approaches for critical analysis of high resolution, complex images (see later for a summary of my reservations). I have always considered, therefore, that there ***ought*** to be a way of carrying out the task efficiently by more direct means. This view is strengthened by my awareness that many extremely critical image comparison tasks are carried out very efficiently by human vision, which most certainly does not employ any Fourier transformation.

Hence, in summary, as I see it, for successful automatic comparison of a pair of fingerprints by 'direct' means (i.e. other than by correlation approaches) it is necessary

- firstly to derive edge maps of local orientation & curvature effectively for each sample image.
- secondly to provide automatic means of aligning (registering) the two edge maps to be compared in both 2D space and orientation.

Possible solutions.

Cross-correlation approach.
Firstly, consider the cross-correlation approach. Without going into technical details (as this is not my own field of research directly), I believe that I am correct in a small number of general statements as follows:-

- Cross-correlation operates in spatial frequency space**.** Hence a fundamental basic necessary step is the carrying out of a 2D Fourier Transform. I am well aware that much software is available nowadays to carry out such a transform. However,
- For a complex image, in order that a high level of sensitivity is to be contained in any 2D Fourier Transform, it is necessary to provide a high spatial frequency resolution in both ***magnitude*** and ***phase*** in two dimensions. I believe this to be definitely a non-trivial requirement. Also, such a transformation should be limited by the sampling interval of the original input images.
- I cannot see that any mis-alignment in position or orientation of the two sample images to be compared is in any sense a trivial matter to handle, even given an adequately high resolution of amplitude and phase in the spatial frequency maps.

SHV-based approach.
How, now, does the approach based on SHV processing fare?

The main processing carried out by SHV is an edge sensing which automatically yields, for each & every detected edge point, the ***sub-pixel*** location of the edge to better than 0.1 pixels, together with the local edge ***orientation*** to better than 1 degree. For images such as fingerprints this yields a very rich & high resolution edge map (and, I would argue, much more information than extracted from a 2D frequency analysis based on single pixel sampling limits). A comparison between 'classical' edge sensing and the SHV approach has already been shown earlier in figures 1 to 5 (for figure 5 it being only possible to show a portion of the full output map without losing information in the resolution of the report!).

For the present purpose, I believe that the ***orientation*** data contained in the high resolution map is the most directly important, since it has been shown possible, using very simple & very local secondary processing, to generate an edge map (and tabulation) of local ***curvature***.(see figure 6 for a high resolution plot of the curvature data - shown for the same image portion as figures 4 & 5). In this figure, curvature is shown as varying shades of grey (darker being locally greater curvature). Such a curvature map I believe to be of fundamental importance in defining (directly) such attributes of fingerprints as whorls etc. (i.e. 'shape' attributes) - the data for every pixel on portions of edges considered 'stable' being fully tabulated.

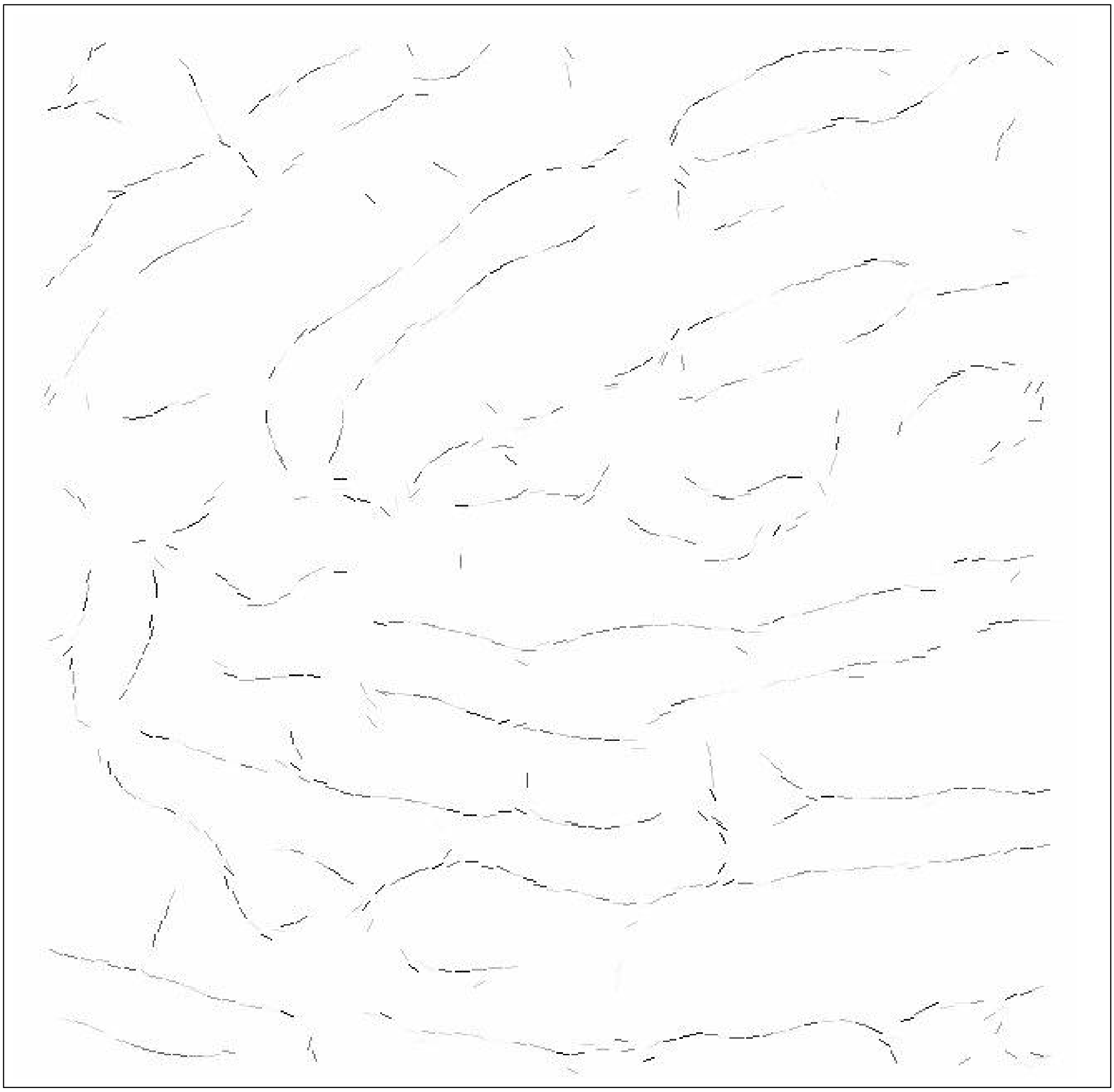

Fig. 6. Sub-pixel local curvature map derived directly from the orientation data contained in figure 5, presented here as varying shades of grey.

Moving on now to the problems of automatic ***comparison*** of a pair of samples, one must address the overall problem of registration (both linear and rotational). For this, I believe the first important requirement is to attempt to remove any differential ***rotational*** mismatch (it seems virtually certain that ther will always be some amount of orientational mismatch between any two samples of a given fingerprint). Now it is possible, by taking the tabulation of local orientations for an entire fingerprint image, to derive a histogram of local orientation distribution. For such things as fingerprints, such a histogram in general will be expected to have characteristic peaks depending strongly on the particular 'shape' characteristics of the print and the 'lay' of the actual image as captured. Figure 7 illustrates a low resolution histogram (10 degree orientation bands) for the image portion for which output data are shown in figures 4 to 6, where it can be seen that there is quite a strong, but relatively smooth, fluctuation with a period of around 180 degrees (i.e. two cycles per 360 degrees, which is as must be expected). If one has two samples of this fingerprint, one should therefore have, readily, a pair of orientation histograms which may be compared in order to determine a mean rotational mismatch - which should then be removed by classical image rotation software.

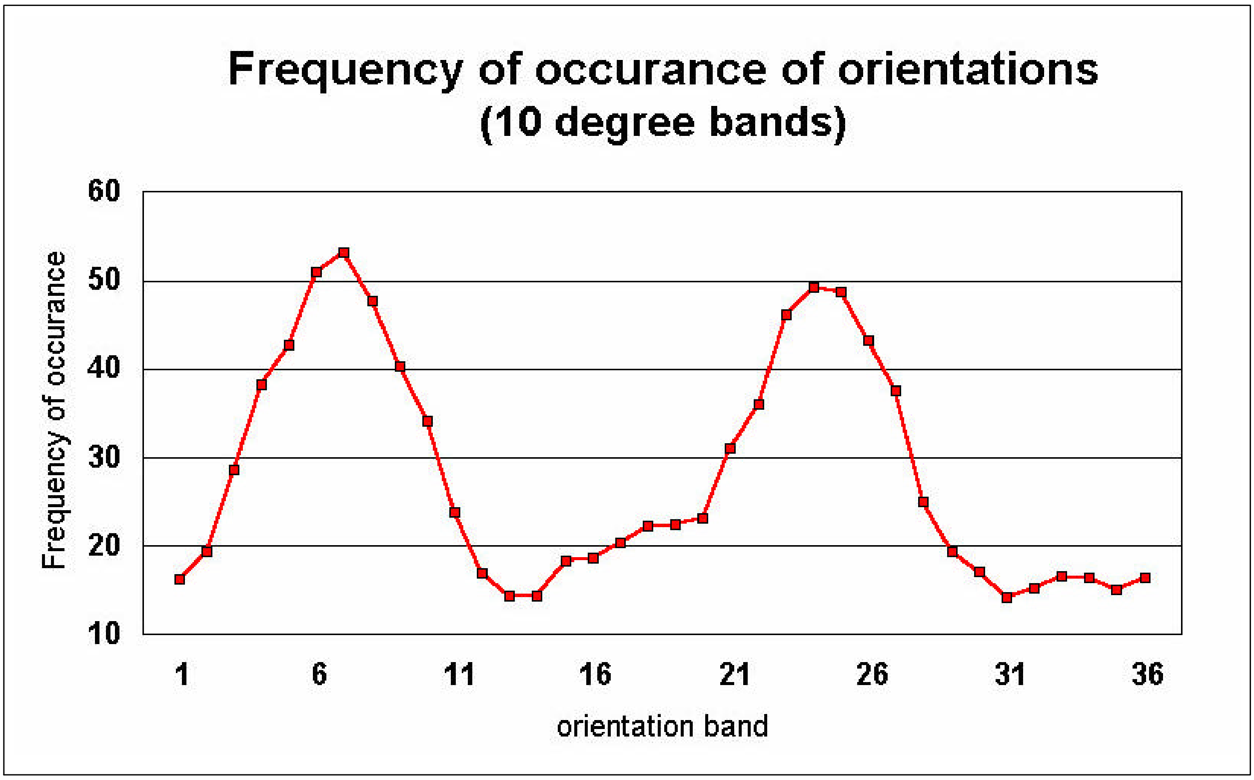

Fig. 7. Histogram of frequency of occurance of local orientations as shown in figure 4.

Having then a comparison pair of images which are best matched for orientation, it is possible to run further simple supplementary SHV software (if necessary firstly on a pair of reduced scale images), whereby analysis of the mean sub-pixel position & orientation of edge fragments can be determined (Ref. 1, Chapter 9 & Ref. 2). In this way, the best mean overlay position for the pair of images can be quickly determined to better than 1 pixel (in 2D).

Having reached this stage, a direct, objective comparison of the ***edge detail*** contained in the two samples can be tackled by one of several methods. My personal choice at present would be the generation of a map of the local ***differences*** between the two images, which ideally should yield an image with zero local fluctuations of grey level. Realistically there will always be ***some*** small local grey level fluctuations, but the magnitude of such fluctuations should be able to be used to set an acceptance level of 'noise' for matching.

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15th November, 2005.

References.

1. Overington I. (1992), "Computer Vision; a unified, biologically-inspired approach", Elsevier North Holland.
2. Overington I. (2003),"Fusion01.pdf".
3. Overington I. (2004), "Canny and SHV comparison.pdf".