A HARRIS CORNER LABEL ENHANCED MMI ALGORITHM FOR MULTI-MODAL AIRBORNE IMAGE REGISTRATION

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Keywords: Image Registration, Maximization of Mutual Information.

Abstract: Maximization of Mutual information (MMI) is a method that is used widely for multi-modal image registration. However, classical MMI techniques utilize only regional and/or global statistical information and do not make use of spatial features. Several techniques have been proposed to extend MMI to use spatial information, but have proven to be computationally demanding. In this paper, a new approach is proposed to combine spatial information with MMI by using the Harris Corner Label (HCL) algorithm. We use the HCL based MMI algorithm to accelerate the computation and improve the registration over noisy images. Our results indicate that the HCL based registration technique yields superior performance on multimodal imagery when compared to its classical MMI based counterpart.

1 INTRODUCTION

The availability of remote sensing imagery from satellites and aircraft using many kinds of imaging sensors has led to the need for robust and efficient multi-modal registration tools. Some imagery examples include low and high resolution still/video cameras in the visual spectrum, multi-spectral cameras using a variety of infra-red wavelengths, imaging spectrometers and synthetic-aperture radar systems. Maximization of Mutual Information MMI (Viola, 1995), initially introduced by Viola, is an automatic registration method for multi-modal images that exploits the underlying inherent information relationships. Compared to cross-correlation, it is insensitive to brightness variations that are inherent across modalities. However, it is somewhat computationally slow and sensitive to image noise. The technique described in this paper will address these shortcomings.

The MMI-based image registration represents an entropy-based measure that does not require the definition of features such as edges or corners and does not employ spatial information that would be available in the form of image features. Researchers have proposed adaptation of the traditional MMI-based registration framework to incorporate spatial information. Butz et al. (Butz and Thiran, 2001) applied Mutual Information (MI) to edge measures defined by different edge operators. However, the attraction range is narrow thereby increasing the difficulty of the optimization procedure. Pluim et al. (Plium et al., 2000) proposed including spatial information by multiplying the MI measure with an external local gradient term. Holden et al. (Holden et al., 2004) registered two images by maximizing the multi-dimensional MI of the corresponding features. Gan et al. (Gan and Chung, 2005) utilized the spatial feature, maximum distance-gradient-magnitude, in a complicated and computationally extensive four dimensional framework for image registration.

In this paper, we introduce a spatial feature-based technique that uses the Harris Corner Label (HCL) algorithm to identify high-information pixels and a wavelet pyramid to support computation at different scales. We propose to calculate the MI from the HCL map of the original images instead of their corresponding intensity values. The experimental results demonstrate that our method is both more robust and efficient than that of traditional MMI registration techniques for multimodal registration. The remainder of the paper is organized as follows. Section 2 provides a brief background on spatial feature infor-

Fan X., E. Rhody H. and Saber E. (2007).
A HARRIS CORNER LABEL ENHANCED MMI ALGORITHM FOR MULTI-MODAL AIRBORNE IMAGE REGISTRATION.
In *Proceedings of the Second International Conference on Computer Vision Theory and Applications - IFP/IA*, pages 420-423

mation and describes our proposed algorithm. Section 3 describes our experimental results. Conclusions are drawn in Section 4.

2 SPATIAL FEATURE INFORMATION

Given an image pair and a geometric transformation, we aim at improving the MMI algorithm by selecting the most relevant pixels for registration purposes. Classical MMI relies only on global statistical information. However, for image registration, it is obvious that edge pixels are more important than those within a nearly uniform region. A focus-of-attention mechanism such as a corner detector provides a excellent avenue to differentiate between these pixel classes.

2.1 Harris Corner Detector

The Harris corner detector (Harris and Stephens, 1988) is a popular interest-point selector due to its strong invariance to rotation, translation, illumination variation and relative tolerance of image noise. It utilizes the average gradient $c(x,y)$ computed over a small region w as follows:

$$c(x,y) = \sum_{w} [I(x_i,y_i) - I(x_i + \Delta x, y_i + \Delta y)]^2 \qquad (1)$$

where (x,y) represent the location of a pixel. This can be expressed in matrix form as

$$c(x,y) \approx \mathbf{d}^T \mathbf{M}(x,y)\mathbf{d} \qquad (2)$$

where $\mathbf{d} = [\Delta x, \Delta y]^T$.

$$\mathbf{M} = \begin{bmatrix} \sum_{w} (I_x(x_i,y_i))^2 & \sum_{w} I_x(x_i,y_i) I_y(x_i,y_i) \\ \sum_{w} I_x(x_i,y_i) I_y(x_i,y_i) & \sum_{w} (I_y(x_i,y_i))^2 \end{bmatrix}$$

and $I_x(x_i,y_i) = I(x_i,y_i) - I(x_i + \Delta x, y_i))$ are gradient measures. Hence, $c(x,y)$ represents the gradient structure of the local neighborhood. The eigenvalues of the matrix $M(x,y)$ are calculated and represented as λ_1 and λ_2. The relationship between them, as depicted in Figure 1, is an excellent indicator of local image characteristics.

Given the above, three cases are customarily considered:

1. If λ_1 and λ_2 are both small, then the local area is relatively smooth.
2. If one eigenvalue is large and the other small, it implies that the local auto-correlation function is ridge shaped indicating a local shift in one direction. This represents a horizontal or vertical edge.
3. If both eigenvalues are large, the local auto-correlation function is sharply peaked, which indicates the presence of a corner.

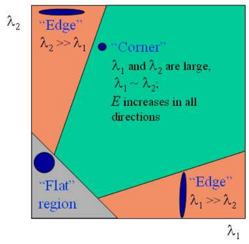
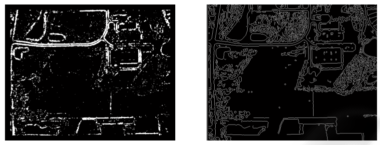


Figure 1: Possible relationships between eigenvalues produced by HCL .



(a) (b)

Figure 2: Comparison between HCL and Canny edge detection.

As a result, we classify pixels by the comparing the eigenvalues to determine which region of Figure 1 applies at each point. Each pixel given a class value of 0, 1, or 2 depending on whether it is in a flat region, near an edge or at a corner.

The Harris corner detector is a good choice as a focus-of-attention for our approach to MMI registration. We tried other focus-of-attention methods such as typical edge detection, but found that the HCL map provides superior performance. The Harris detector, in effect, identifies a rich set of pixels that can be used in the MMI computation. This can be easily seen in Figure 2.

To achieve the effect of focusing on areas that have high information content, our algorithm applies MMI to the HCL map of the images instead of the original intensity. Because it is computed from the local auto-correlation map, HCL also provides a level of filtering. This property helps to increase the capture range in the registration procedure.

2.2 Mmi on Hcl Mapping

In our implementation of the MI-based multi-modal image registration, MI is computed on imagery that has been pre-processed by the HCL. To this effect, a Harris Corner Detector is utilized to divide all pixels into three categories: inside pixel, edge and corner. The joint histogram calculation among the labels has

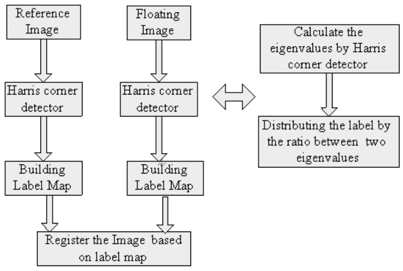


Figure 3: Flowchart for the HCL-Based MI registration.

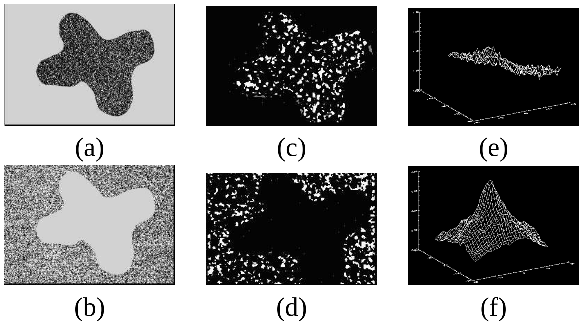


Figure 4: Noisy image registration Example: (a) and (b) represent two noisy images; (c) and (d) shows the HCL mapping for two images; (e) and (f) shows the search surface for conventional MMI and HCL-enhanced MMI registration algorithm.

a smaller range of values to consider than the calculation based on the intensity. In addition, we use a 4-level-wavelet-pyramid to accelerate the registration process and increase its robustness.

3 EXPERIMENTAL RESULTS

In this section, we present two sets of experiments. The first set is utilized to test the robustness of HCL-based MI with regard to noise. The second set is employed to evaluate the performance of our proposed method relative to traditional MI-based registration.

3.1 Synthetic Images

Although conventional MMI is very powerful, its performance is reduced in images with large regions of uniform intensity and regions of high randomness. This can be demonstrated by an extreme case. In Figure 4, we show an image of a noisy object on a flat background and vice versa. In Figure 4a, the background is constant, and the object has spatially independent random pixels. Figure 4b has a reversal of the structure in Figure 4a. When Figure 4a and Figure 4b are aligned, every random pixel in one image is constant in the other and vice versa. This makes the pixels in one image statistically independent of its counterpart in the other image. Hence, any misalignment leads to overlaps of like regions which poses significant challenges for conventional MMI registration.

On the other hand, the images shown in Figure 4 are easily processed by a HCL-Enhanced MI. Although the pixel intensity is random inside the region, sufficient gradient information is detected to enable MMI registration. Figure 4c and d show the HCL map at one of the pyramid layers. Figure 4e depicts the resulting MMI surface achieved from Figure 4a and 4b, as a function of horizontal and vertical shifts, while Figure 4f represents the MMI surface achieved with Figure 4c and d. As can be easily seen, the MI surface obtained from the HCL based technique is far well suited for registration that its counterpart.

Table 1: WASP camera description.

	Bandwidth	Resolution
SWIR	0.9-1.7 μm	640×510
MWIR	3-5 μm	640×510
LWIR	8-9.2 μm	640×510
VNIR	0.4-0.9 μm RGB	2048×2048

3.2 Real Life Multimodal Images

The real life multimodal images used in this section were captured by the Wildfire Airborne Sensor Platform (WASP) system, which includes three IR cameras and a high-resolution visible camera. The specifications of the system are shown in Table 1.

3.2.1 Intra-band Registration

The images shown in Figure 5a and 5b represent two frames taken 4 seconds apart from the short wave IR band of the WASP system. Figure 5c shows the corresponding registration curves for the two algorithms, where the solid is for HCL-MMI algorithm and the dashed is for the conventional MMI. The registered images are overlaid (See Fig. 5d to indicate the high degree of accuracy obtained by our proposed approach. [1]

3.2.2 Inter-band Registration

In this section, we demonstrate the effectiveness of the HCL-MMI algorithm in registering multi-modal imagery acquired by the WASP system using the three IR bands discussed in Table 1. The short, medium and

[1] The running environment is P4 3.0G 1G RAM, IDL 6.0

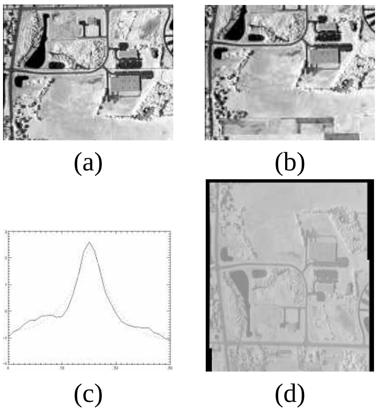


Figure 5: Intra-band Registration Example: (a) and (b) represent two sequential frames, (c) Registration Curve for two algorithms, (d) Overlaid registered images.

Table 2: Results for WASP Intra-band Registration.

	Conventional MMI			HCL-Enhanced MMI		
θ	*x*	*y*	Time (s)	*x*	*y*	Time (s)
0	-8	237	14.04	-8	237	7.753
0	65	232	12.765	65	232	7.422
0	10	104	11.547	10	104	6.656
-0.5	19	-236	71.75	19	-236	39.329
0.5	27	-251	84.26	27	-251	45.23
0	4	-246	15.531	4	-246	7.859

long IR images are shown in Figure 6a, b and c respectively. Note the translation, scale and significant intensity variations. The results computed by our algorithm are shown in Fig. 6d and displayed in Table 3, where the short wave band was utilized as the base image.

From the above examples, we can see, relative to the conventional MMI algorithm, that the HCL-MMI algorithm can reach the same accuracy in about half the computing speed. This was found to be true for many other examples that have been tested.

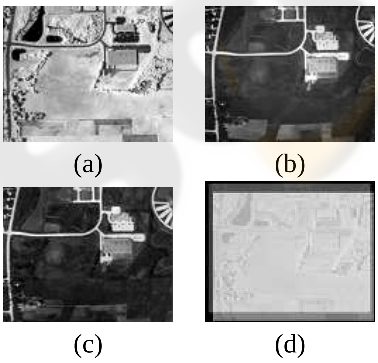


Figure 6: Inter-band Registration Example.

Table 3: Inter-band Registration Results.

	Conventional MMI				HCL-Enhanced MMI			
	scale	*x*	*y*	time	scale	*x*	*y*	time
MWIR	1.13	19	32	51.06	1.13	19	32	29.68
LWIR	1.12	6	36	46.16	1.12	6	36	26.6

4 CONCLUSION

In this paper, we proposed a HCL-based MMI algorithm for registering multi-modal images. The HCL-based MMI is reliable and efficient. The Harris corner label improves robustness as demonstrated with various synthetic and real life images. Because the Harris corner detector is invariant to the translation and rotation, the HCL-MMI algorithm can register images with shift, rotation and scale differences. The Harris corner detector broadens the attraction range and, in our experience, reduce the risk of being trapped in a local minimum. Experimental results show the algorithm is successful in registering IR with visual images. The use of a multi-resolution technique increases robustness by enabling computation at an appropriate scale.

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