ROBUST REGISTRATION OF SATELLITE IMAGES WITH LOCAL DISTORTIONS

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1. ABSTRACT

Registration of satellite images is relevant to many applications in the context of multispectral classification, environmental monitoring, change detection, weather forecasting. The process consists in the geometrical alignment of a slave and a master image of the same scene, taken at different time instants and, in general, involves four steps: (a) feature detection, (b) feature matching, (c) transform model estimation, (d) image resampling and transformation. Feature matching and transform model estimation are the most critical points and, in great part, determine the final performance of the registration process. In this work we present some new results in the field of area-based feature matching and adaptive transform model estimation.

Template matching based on Entropy of Difference-image

In this stage, a template area is compared with the corresponding area in the master image and a two-dimensional shift is applied so as to maximize some similarity measure over all potential candidate matches. The choice of the similarity measure is a main issue. Mean Square Difference and Normalized Cross Correlation are commonly used but they may become unreliable in the presence of local image changes. A more robust measure is the Mutual Information (MI) that is able to catch nonlinear statistical dependencies, exhibits some robustness against noise and local deformation, and is invariant to amplitude scaling [1]. On the other hand, the accuracy of MI estimation is related to the possibility of obtaining good estimates of the joint probability density function (pdf) of the data. Several methods can be used to this end: Partial and General Volume Estimation [2], Adaptive Partitioning [3], Kernel Density Estimation [4]. In any case, it is clear that the problem becomes more and more complex as the number of dimensions increases and the sample dimension decreases. The two-dimensional problem is, nonetheless, non trivial and the final estimate can be very poor if the solution is attracted towards a local extremal point. In this study we introduce the Entropy of Difference–image as a similarity measure. This is a measure in one dimension and its estimation is accurate even for small data sets and less sensitive to local minima, but it is yet robust to local image distortions. The use of the difference image is motivated by the fact that, for optimal registration of master and slave templates, the difference image exhibits low variations, whereas in the case of misregistration the contrast variation becomes larger. Because the entropy is the minimum description length of a random variable, it can be used as similarity measure for the difference image. The lowest value of the entropy of the difference image corresponds to optimal registration. An application of this concept can be found in [5, 6] where an histogram–based entropy estimation is used for registration of medical images.

Starting from this encouraging result, we have derived a fast and accurate algorithm for template matching of high–resolution satellite images based on Entropy of Difference-image. The algorithm is based on a very efficient and accurate stage for pdf estimation which is based on a Gaussian Mixture Model for the pdf. The model is quite general and tightly fits the model underlying a difference image, where the data are expected to accumulate around two center values: one around zero for the matching data and one around a non-zero value where some distortion or change arises. A final comparison of the achieved results with those obtained from other registration measures is presented by resorting to simulated deformations. Figure 1 shows a plot of the entropy as a function of the shift along the $x - y$ axis, where it is apparent the presence of a sharp peak corresponding to the images matching.

Thresholding and Transform Model estimation

The mapping of the slave image to the master one is represented by a field of displacement vectors. Each vector indicates the (x, y) optimum displacement of the block center. Block centers are usually one pixel apart each other, indeed the displacement map has the same size of the original images (apart from border effects). The vector field can be, in any case, affected by errors due to local changes between the master and the slave template or local distortions due to the changed observation geometry. The classical Transform Model estimation is based on a polynomial fitting of the $(x-y)$ vector coordinates. This procedure plays the role of regularizing the vectors field but implicitly introduces the constraint that the distortion function is tightly approximable with a polynomial. A more flexible and weaker constraint is to introduce a vector regularization based on a diffusion equation as in [4]. We propose here, an alternative point of view, where the regularization is carried out in two stages: a thresholding

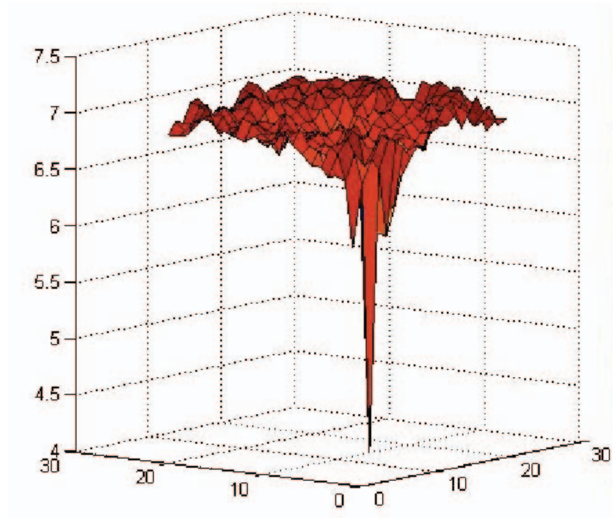

Fig. 1. Entropy of Difference-image vs. shift.

stage and an inpainting stage. The thresholding stage is designed to retain the most reliable vectors while marking as holes the unreliable vectors. The holes are subsequently restored using a complex Ginzburg–Landau inpainting. This equation was developed by Ginzburg and Landau to model phase transitions in superconductors near the critical temperature and has been recently applied to image restoration [7]. In this case, it is used to fill the holes of the vector field through a reaction–diffusion mechanism where the diffusion evolves mostly along edges and not across.

2. REFERENCES

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