

Robust Model Based Motion Segmentation

Alireza Bab-Hadiashar¹, Niloofar Gheissari² and David Suter³,

^{1,2}School of Engineering & Science, Swinburne University of Technology, Hawthorn Vic, 3122, Australia

³Department of Electrical & Computer Systems Engineering, Monash University, Clayton Vic, 3168, Australia

Email: abab-hadiashar@swin.edu.au, ngheissari@groupwise.swin.edu.au, d.suter@eng.monash.edu.au

Abstract

This paper presents a new algorithm for the motion segmentation task. The proposed algorithm addresses the important issue of the interconnectivity between data segmentation, model selection and noise scale estimation. The algorithm is tested on motion segmentation of multiple objects undergoing different types of motion. The results of applying our algorithm to range data segmentation are also included.

1. Introduction

A broad spectrum of computer vision applications depend upon accurate and reliable data segmentation algorithms. In particular, motion segmentation is an important part of many robotic applications: such as tracking and path planning.

A novel approach to visual data segmentation is presented in this paper. The proposed method deals with the two crucial issues of data segmentation: model selection and noise scale estimation, simultaneously. Generally speaking, the proposed algorithm can be categorised as a parametric (model based) technique although some of its steps make use of spatial information (for sampling and model selection).

The rest of this paper is organised as follows. We briefly review some of the visual data segmentation literature in section 3. As our proposed method relies on model selection criteria, we dedicate section 2 to the analysis of different model selection criteria in motion segmentation context. A brief overview of motion and range segmentation literature is provided in sections 3 and 4. The procedure for estimating the scale of the noise is described in section 5. In section 6, the proposed segmentation algorithm is explained and the results of our experiments on motion and range data segmentation are presented in section 7. Section 8 concludes the paper.

It should be mentioned that the segmentation algorithm described in section 6 is an improvement of our previous work [2] by adding some stages to incorporate a model selection criteria in the segmentation process. The paper also includes a survey of different model selection criteria.

2. Model Selection

In all the parametric image segmentation algorithms, one needs to find the most appropriate model which would best fit the data. Therefore, a suitable *model selection criterion* should be viewed as an important part of any parametric segmentation algorithm. We have investigated a wide range of model selection methods including: AIC, G-AIC, CAIC, CAICF, CP, SSD, BIC, MDL, G-MDL, GBIC, BMSC-BAYES for motion segmentation and we have concluded that G-MDL (proposed by Kanatani [7]) performs better than any of the above techniques (see [3] for more details).

2.1. Testing Different Model Selection Techniques

To compare the performance of different model selection techniques, we have generated four sets of synthetic image sequences in which the underlying motion of their intensity patterns are known. The models of motion used were: constant, affine, partial-quadratic and quadratic as show in table 1. We then changed the parameters of every model 100 times and applied the model selection criteria to test how well it identified the underlying model.

Model	Horizontal and Vertical Velocities
Constant	Constant
Affine	$ax + by + c$ & $cx + dy + e$
Partial Quadratic	$ax^2 + bxy + cx + dy + e$ & $by^2 + axy + fx + gy + h$
Quadratic	$ax^2 + bxy + cy^2 + dx + ey + f$ & similar for the other flow component

Table 1: Model library

Figure 1 shows the average success rate of different model selection techniques when they are applied to the motion segmentation problem. As can be seen in this figure, Kanatani's GMDL appears to be more successful than others regardless of the fact that we either use geometric or algebraic distance for error measurement. The GMDL criteria can be expressed as:

$$\sum_{i=1}^n r_i^2 - (Nd + P)\delta^2 \log(\delta / L)^2$$

Where N is the number of data points and P is the number of parameters in the model. L, the reference length is calculated by N^2/δ^3 (δ is the scale of the noise).

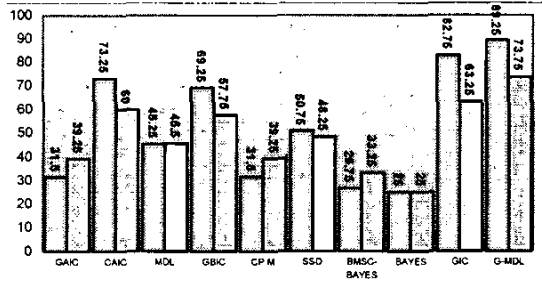


Figure 1 Comparison of the different model selection techniques for motion segmentation. The filled columns represent the results of using algebraic distance while the hatched columns represent the geometric distance results.

3. Motion segmentation

Motion segmentation is defined as the task of partitioning a sequence of images based on the coherent motion of different objects in a dynamic scene. Motion segmentation algorithms are broadly classified into three groups.

- *Optic flow based segmentation.*

In this approach [4] the optic flow field is computed and a motion model is fitted to the optic flow field. Geometry of the scene can be used to combine this approach with a region growing approach.

- *Simultaneous or sequential recovery of motion and segmentation.*

In these techniques, the segmentation is often formulated by using a Markov Random Field (MRF), which is a way of incorporating spatial correlation into a segmentation process. The MRF specifies the local characteristics of an image and uses the given data to reconstruct the true image. Peleg and Rom [10] have proposed a segmentation algorithm based on this approach.

- *Fusion of motion recovery and static segmentation.*

In these techniques, a statistical measure derived from the intensities of objects in every image is added to the motion information to enhance the segmentation results. Thompson [11] was the first one to use a similarity constraint on brightness and motion to achieve motion segmentation using a region-merging algorithm. Black [5] proposed a segmentation algorithm by formulating a model of physically significant image regions using local constraints on intensity and motion and then finding the optimal segmentation over time.

More recently, Kanatani [8] presented a robust segmentation algorithm by incorporating a reformulated Costerica-Kanade algorithm independent of Tomasi -Kanade factorization. He used the geometric AIC (GAIC) for model

selection and the least median of squares for model fitting. Kanatani also presented techniques for evaluating the reliability of segmentation[9]. Torr has also developed algorithms for clustering features that belong to independently moving objects in the presence of noise and outliers [12]. The main difference between the above works and the one presented here is that those algorithms are feature based and used a sparse set of features to identify the objects. Therefore, the number of data is relatively small. In our approach, we rely on the texture of the moving object and therefore the segmentation involves fitting models to a large data set.

Colour information has also been used for enhancing the motion segmentation[1]. This kind of technique is application dependant and therefore has limited use.

4. Range Segmentation

Range segmentation is a well-known problem in Computer vision. Segmentation of a range image is the process of classifying each pixel so that different pixels, which belong to the same real surface, are put in the same class (see [6] for a detail discussion of range data segmentation algorithms). Although the algorithm presented here is developed for motion segmentation task, we also present the result of a few experiments with range data. Range data, compared to visual motion data, has less noise and outliers and therefore is useful for testing purposes.

5. Estimation of Scale

One of the most important elements of our motion segmentation algorithm is the process by which the scale of the noise is estimated. Here, we use a procedure which is based on the MSSE [2] and consists of following steps:

1. Sort the squared residuals in an ascending order and choose the size of the smallest structure K, which can be regarded as a separate structure.
2. Set the value of n (initially to K) and calculate the

scale using the first K^{th} residuals using: $\delta_n^2 = \frac{\sum_{i=1}^K r_i^2}{n-p}$

where p is the dimension of the model.

3. Increase the value of n and repeat step 2 until $\frac{\delta_{n+1}^2}{\delta_n^2} > 1 + \frac{T^2 - 1}{n - p + 1}$ is no longer true.

T is a constant factor and we set it to 2 in order to include about 95% of our normal assumed distributed data as inliers. The performance of the algorithm is not very sensitive to this value.

4. Compute the scale by using the final value of n as performed in step 2.

6. Segmentation Algorithm

In this section, we briefly, but precisely, explain the steps of the proposed motion segmentation algorithm. The proposed method is based on the Selective Statistical Estimator [2] and GMDL [7]. The required steps are as follows:

1. Eliminate pixels whose spatial or temporal derivatives are less than a threshold. The threshold for spatial derivatives is set at 0.03%, and for temporal derivatives is set at 0.15%, of the average derivatives. This step removes points without motion or texture (contains no motion information).
2. Find a localised data group inside the image data in which a group of pixels have a constant velocity (with small variance). To implement this stage, the algorithm chooses a random point as the centre of a square and computes the optic flow by implementing LMS to the obtained system of over-determined equations (optic flow constraints for all the pixels of that square).
The size of square is not important however it needs to be big enough to contain enough sample points. We set the square size as 15×15 in our experiments.
3. Fit a partial quadratic model to the above data group and find the residuals for all the points (assuming that there is small plane undergoing rigid motion where the seed is found). We will then repeat the above two steps and accept the data group, which has the least K^{th} order residual (the choice of K depends on the application[2]). In the above stages, we have to be very conservative to find a reliable initial grouping of the data.
4. Fit the most general model (in our experiment the quadratic model of motion) to the data group (section 2,3).
5. Find the scale of noise for the above fit using MSSE (section 5) and eliminate the outliers. We normally apply a median filter with a small window (15 square wide), in this stage, to remove stray points that might have similar motion. These two last stages identify a region of inliers.
6. Expand this region by repeating step 4 and 5 for a couple of times. These two steps will help to obtain a larger (and, at the same time, more reliable) area to apply the model selection technique.
7. Apply a model selection method (here GMDL) to the selected patch (by fitting all the other models of the model library to the extended region) and find the appropriate model.
8. Fit the chosen model to the data and compute the residuals.
9. Estimate the scale of noise by using MSSE [2].
10. Establish a group of inliers based on the obtained scale and recalculate the residuals.

$$11. \text{ Compute the final scale using: } \delta_n^2 = \frac{\sum_{i=1}^n r_i^2}{n-p}.$$

12. Apply a hole-filling (median filtering) algorithm to remove holes resulting from discontinuities of the intensity function (erroneous derivative value).
13. Repeat the steps 2 to 12 until the remainder of the data becomes less than the size of the smallest structure (assumed to be the threshold for importance) in the considered application.

7. Segmentation Result

In this section, we present the motion segmentation results of applying the proposed algorithm to a synthetic and a real image sequence. We also include the result of segmenting some range data by the proposed algorithm (the range segmentation algorithm is similar to the above motion segmentation algorithm and it is explained in [3]).

7.1. Synthetic Image Segmentation

To demonstrate the theoretical performance of the proposed segmentation algorithm, a synthetic image sequence with different patterns of motion is generated. Every image of this sequence is a 150 by 150 pixel image made of four quadrants with independent motions. The top right corner has an affine velocity, the top left corner has a quadratic velocity, the lower right corner has a partial quadratic velocity and the lower left corner exhibits constant velocity motion. The texture for all of the segments is a sinusoidal pattern created by superimposing two 2-D sinusoidal plane-waves with the spatial wavelengths of 6 pixels and orientations of 54 and -27 degrees [4]. The derivatives of the intensity function are calculated by convoluting the image with the derivative of a unit Gaussian function. The following picture shows a sample image and the final segmentation result.

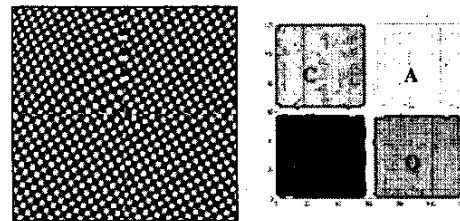


Figure 2: A sample image of our sinusoidal sequence and the final segmentation result (every returned segment is shown with a different shade of gray- and unresolved data is depicted as white pixels). The capital letters identify the model predicted by the proposed technique.

7.2. Real Image Segmentation

In this section, we present the results of our approach applied to the Rubik cube sequence (created by Richard Szeliski). In this image sequence, a *Rubik* cube is placed on a turntable, which is rotating in front of a stationary background. The velocities on the turntable are around 1.2 to 1.4 pixels/frame and on the cube itself are around 0.2 to 0.5 pixels/frame.

The Rubik cube sequence is particularly a good example; mainly because the projected motion of its planar surfaces is well described by the partial and full quadratic models of motion. The rigid motion of its planar surfaces (cube faces) are described by a partial quadratic while the motion of the quadratic face of the turntable can be explained by a full quadratic model of motion. A snapshot and the segmentation results for this sequence are shown in figure 3. It can be seen from these pictures that the segmentation has been able to correctly identify different moving part and more importantly has also been able to correctly identify the underlying model of each part.

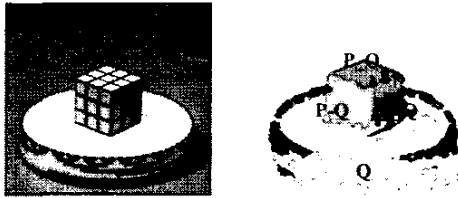


Figure 4: Result of our Motion Segmentation. Q indicates that the selected model is Quadratic while P-Q indicates that the chosen model is partial quadratic (based on the GMDL criteria).

7.3. Range Data Segmentation

For range segmentation experiments, we have chosen an object which is a combination of planar and quadratic surfaces. For this experiment, we have chosen a library of models from f_1 to f_4 . The following figure shows the results of the proposed algorithm.



Figure 5: Range Data Segmentation. The letter over each segment indicates to the chosen model by G-MDL.

$$f_1(x, y, z) = ax^2 + by^2 + cz^2 + dx + ey + fz = 1$$

$$f_2(x, y, z) = ax + by + cz + dxy + exz = 1$$

$$f_3(x, y, z) = ax + by + cz + exy = 1$$

$$f_4(x, y, z) = ax + by + cz = 1$$

8. Conclusion

In this paper, we have proposed and tested a new robust motion segmentation algorithm. The important aspect of this algorithm is its capability to recover the underlying model motion and scale of noise while performing the segmentation. The proposed algorithm is tested on synthetic and real image sequences and has shown to be effective.

Reference List

- [1] Altunbasak, H., Eren, P. E., and Tekalp, A. M., Region-Based Parametric Motion Segmentation Using Color Information, *Graphical Models and Image Processing: GMIP*, vol. 60, no. 1, pp. 13-23, 1998.
- [2] Bab-Hadiashar and Suter D., Robust Segmentation of Visual Data Using Ranked Unbiased Scale Estimate, *ROBOTICA, International Journal of Information, Education and Research in Robotics and Artificial Intelligence*, vol. 17, pp. 649-660, 1999.
- [3] Bab-hadiashar, A., Suter, D., and Gheissari, N., "Report on Model Selection methods for segmentation Algorithms," Swinburne University of Technology, Melbourne, Australia, 2001.
- [4] Barron, J. L., Fleet, D. J., Beauchemin, S. S., and Burkitt, T. A., "Performance of Optical Flow Techniques," *Proceedings of CVPR'92*, Washington, pp. 236-42, 1992.
- [5] Black, M., "Combining Intensity and Motion for Incremental Segmentation and Tracking over Long Image Sequences," *Second European Conference on Computer Vision*, pp. 485-493, 1992.
- [6] Hoover, A., Jean-Baptist, G., Jiang, X., J.Flynn, P., Horst, B., Goldgof, D., Bowyer, K., Fggert, D., Fitzgibbon, A., and Fisher, R., An Experimental Comparison of Range Image Segmentation Algorithms *IEEE Transaction on Pattern Analysis and Machine Recognition*, vol. 18, pp. 673-689, Jul, 1996.
- [7] Kanatani and Kenichi, "Model Selection for Geometric Inference," *The 5th Asian Conference on Computer Vision*, Melbourne, Australia, pp. xxi-xxxii, January 2002.
- [8] Kanatani, k., "Motion Segmentation by Subspace Separation and Model Selection," *Proceedings of the 8th International Conference on Computer Vision, (ICCV 2001)*, Vancouver, Canada, pp. 301-306, July 2001.
- [9] Kanatani, K. and Matsunaga, C., "Estimating the Number of Independent Motions for Multibody Motion Segmentation," *Proceedings of the 5th Asian Conference on Computer Vision (ACCV 2002)*, Melbourne, Australia, pp. 7-12, Jan. 2001.
- [10] S. Peleg and Rom, H., "Motion based segmentation," *IEEE International Conference on Pattern Recognition*, Atlantic city, NJ, pp. 109-113., 1990.
- [11] Thompson, W. B., Combining Motion and Contrast for Segmentation *IEEE TPAMI*, vol. 2, pp. 543-549., 1980.
- [12] Torr, P. H. S., Geometric motion segmentation and model selection *Phil. Trans. Roy. Soc.*, vol. A-356, pp. 1321-1340, 1998.