FEATURE POINT MATCHING USING TEMPORAL SMOOTHNESS IN VELOCITY

I.K. Sethi, V. Salari and S. Vemuri

Department of Computer Science
Wayne State University,
Detroit, MI-48202, U.S.A.

Abstract

One of the vital problems in motion analysis is to match a set of feature points over an image sequence. In this paper, we solve this problem by relying on continuity of motion which is known to play an important role in motion perception in biological vision systems. We propose a relaxation algorithm for feature point matching where the formation of smooth trajectories over space and time is favored. Experimental results on a laboratory generated as well as a real scene sequence are presented to demonstrate the merit of our approach.

1. Introduction

One of the vital problems in motion analysis is to match a set of physical points over an image sequence representing a dynamic scene. This problem is called the correspondence problem and the physical points are often referred to as tokens or feature points. The correspondence problem is an integral part of many important vision tasks such as object tracking [23], event detection and motion interpretation [5,16], and the token based recovery of object structure from motion [22].

Traditionally the correspondence problem has been solved using two frames of the dynamic scene [1,13,15]. Invariably these approaches impose a rigidity constraint on the feature point configuration to obtain the correct correspondence. This is due to the fact that these approaches implicitly assume a situation analogous to the long range motion process of the human visual system [2,3]. Under the long range motion process, the motion stimuli has a large separation in space and time. Consequently the rigidity of objects provides a powerful constraint on possible solutions for correspondence. The assumption of rigidity allows the use of the spatial smoothness of disparity vectors, thus providing a supporting hypothesis for relaxation algorithms to converge to the correct correspondence [1,13,15]. In fact some of the correspondence algorithms using only two frames and the rigidity constraint are also applicable to stereo matching. This clearly indicates that although these algorithms have a much wider applicability, the real use of motion information is not made. Sethi and Jain [17] refer to two frame approaches as quasi-dynamic scene analysis approaches and argue in favor of more realistic dynamic scene analysis techniques.
For a more realistic use of motion information it is required that we would look at an image sequence acquired over a period of time by sampling the scene at a fairly rapid rate. There are numerous psychological studies [10,14,21] which support the use of motion information over an extended period of time. With continuous motion of physical objects and rapid scene sampling we obtain a situation similar to the short range motion process of the human visual system. This is the motion perception phenomenon which is exploited in cinematography. Continuity of motion is the dominant factor in short range motion perception and it even allows the human visual system to fill-in the gaps when the motion stimuli is presented in a discrete manner [20]. Recent works of Jenkin [8], Jenkin and Tsotsos [9], and Sethi and Jain [17] are examples of exploiting motion continuity to establish correspondence of feature points in a dynamic environment. Input to the system in the case of Jenkin and Tsotsos is a pair of stereo images captured at regular short time intervals. The objective is to match feature points in stereo as well as in time. Because of the use of a stereo pair, Jenkin and Tsotsos use the temporal smoothness of the velocity of feature points in three dimensional space to guide the matching process. A spatial proximity rule is used to help the matching process by limiting the set of possible matches. Sethi and Jain address the problem of feature point correspondence in a monocular image sequence and the smoothness of velocity in the temporal domain in their case refers to the projected two dimensional velocities of the feature points. Smoothness of velocity in the image plane is used by Sethi and Jain to look for an optimal set of smooth trajectories by way of solving an optimization problem. Hildreth’s work [7] on the computation of optic flow vectors along moving contours is another example of motion measurement under the short range motion process. Since the line constraints equation for optic flow provides a single equation involving two unknowns at each point on the moving contour, Hildreth suggests a minimization procedure to obtain optic flow vectors. The criterion function for minimization is based on the assumption of spatial smoothness of velocity vectors which Sethi and Jain [18] have shown to be equivalent to the assumption of temporal smoothness of velocity under the short range motion process.

One important issue which is often overlooked in all the correspondence work is the reliability of the feature point detection algorithms. Our experience with laboratory and real scene image sequences indicates that none of the feature point detectors currently available in the literature [4,11,12,19,24] are capable of yielding a satisfactory set of feature points consistently. Thus, if we want a correspondence algorithm to work well, we should either look for a rugged and reliable feature point detector for real images or the correspondence algorithm should be tailored to meet the vagaries of the real scene data. It is the second approach that we have adopted in the present work. Using the hypothesis of smoothness in motion in time as in [17], we present in this paper a relaxation algorithm for obtaining feature point correspondence. Initial confidence match values for feature points are computed using the path coherence function of Sethi and Jain. These match values are then iteratively updated to obtain a smooth set of trajectories indicating the feature point matches. The updating is done using the support provided by the temporal smoothness of motion hypothesis described in Section 2 of the paper. Section 3 describes the relaxation algorithm using this hypothesis. Experimental details are given in Section 4 to indicate the merit of the hypothesis.