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An ant colony optimization based stereoscopic particle pairing algorithm for three-dimensional particle tracking velocimetry

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ABSTRACT

An ant colony optimization (ACO) based stereoscopic particle matching algorithm has been developed for three-dimensional (3-D) particle tracking velocimetry (PTV). In a stereoscopic particle pairing process, each individual particle in the left camera frame should be uniquely paired with the most probable correct partner in the right camera frame or vice-versa for evaluating the exact 3-D coordinate of the particles. In the present work, a new algorithm based on an ant colony optimization has been proposed for this stereoscopic particle matching. The algorithm is tested with various standard 3-D particle image velocimetry (PIV) images of the Visualization Society of Japan (VSJ) and the matching results show that the performance of the stereoscopic particle pairing is improved by applying proposed ACO techniques in comparison to the conventional nearest-neighbor particle pairing method of 3-D stereoscopic PTV.

1. Introduction

Hot-wire anemometry is one of the oldest techniques for the measurement of the quantitative information of the flow field. This technique is intrusive and was partially replaced and complemented by laser doppler anemometry (LDA), a non-intrusive optical technique. Both techniques offer the possibility to measure all three components of the velocity vector but only at one or several locations. Though these methods still retain some important positions in the field of experimental mechanics, in recent years, particle image velocimetry (PIV) has been widely accepted as a reliable whole-field velocity measurement technique in every branch of fluid engineering [1]. The recent mode of PIV is 3-D and the main trend of the current 3-D PIV is a stereoscopic extension of a standard 2-D PIV system, using a finite-thickness laser light sheet and two stereoscopic CCD cameras in Scheimpflug optical arrangement [2]. However, the measurement target of this type of 3-D PIV system is limited to 3-D flows with comparatively small out-of-plane velocity components with respect to the two in-plane components [3]. Under these circumstances, the 3-D particle tracking velocimetry (PTV) [4,5] is probably a more promising technique than the stereoscopic 3-D PIV using a finite-thickness laser light sheet for the full-volume 3-D flow measurements because the depth velocity component is also as well resolved as other components.

The 3-D PTV is composed of two successive steps of particle pairing [6] as shown in Fig. 1. The first one is the co-instantaneous spatio-differential (parallactic) particle pairing, in which the particles viewed by two (or more) stereoscopic cameras with different viewing angles have to be correctly paired at every synchronized time stage. This is necessary for computing the 3-D coordinates of individual particles. The second one is the time-differential particle pairing, in which the particles with computed 3-D coordinates have to be correctly paired with those at the next time step. Of these two steps of particle pairing, the second one is relatively rich in methodology because many of the known two dimensional (2-D) time-differential tracking algorithms [7–11] can be extended into 3-D tracking without any additional complexity. However, the first step, i.e., the spatio-differential particle pairing process encounters difficulties and possesses some challenges when accurate estimation of 3-D particle coordinates is required. The main issue comes from the fact that two neighbor particles in the camera images are not necessarily located close to each other in real 3-D space. In this context, the most commonly used method for this spatial particle pairing is the epipolar line nearest neighbor analysis [12]. But this method does not produce a high recovery ratio of 3-D particles in densely seeded particle images. The principal reason for this is the fact that in a volume with densely seeded particles, there arise plenty of epipolar lines with which the nearest neighbor particles do not make correct particle pairs. Another difficulty in stereoscopic particle pairing arises from the fact that the algorithm in principle is not allowed to profit from the information of the neighbor particles as in the case of the time-differential particle pairing. In this respect, the use of a third or even a fourth stereoscopic camera avoids the ambiguous pairing

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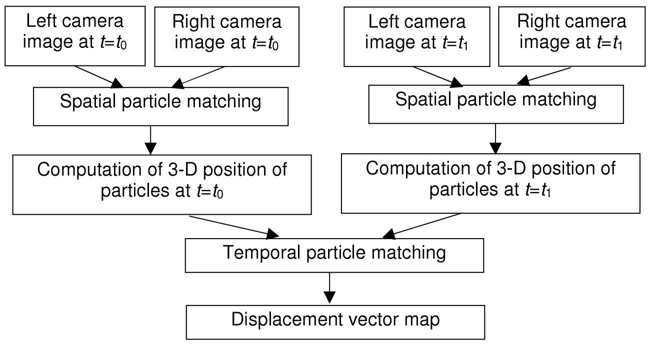

Fig. 1. Typical flow chart of 3-D particle tracking velocimetry.

and increases the recovery ratio of 3-D particles. But the use of an additional camera adds another complexity in the process of particle pairing in terms of the requirement for more expensive and sophisticated hardware. Besides, the numbers of particles viewed by three or more cameras are also decreased as each camera has its own limited view area. What is then needed is a new powerful algorithm which gives better particle pairing results even with a two camera arrangement.

With such a view, some advanced computational techniques for the stereoscopic particle matching problem have been reported by some authors using only a two camera arrangement. Grant et al. [13] suggested a Hopfield neural network based computational strategy. This is an interesting attempt with a concept of the minimization of Lyapunov energy function, but in their approach the camera configuration is restricted in such a way that the object plane, lens plane and image plane all need to be parallel to each other, and the lens of the cameras must be in the same plane. In this kind of translational configuration, there is not enough flexibility to resolve the depth. Moreover, the Hopfield neural network approach is not a good choice for the particle tracking velocimetry when the particle number exceeds 150 particles per frame [14,15]. Similarly, Doh et al. [16] applied the genetic algorithm (GA) for 3-D stereoscopic particle tracking velocimetry with successful results, but their strategy was a simultaneous optimization of the spatial and temporal particle pairing between two time-differential sets of two (or more realistically three) stereoscopic particle images. The results of their flow analysis seem interesting but the applicability of the genetic algorithm for simultaneous two-stage particle pairing is rather obscured. Further, the neural network based on the self-organizing maps (SOM) method [17] and cellular neural network (CNN) method [18] using two camera arrangement was applied for the stereo PTV. In the case of SOM, the algorithm works well with larger number of particles but the computation of the initial distance parameter is difficult and the stereo PTV results are sensitive to this computation parameter. If the value of this initial distance parameter is large, the algorithm will take a large amount of time to converge whereas if the value is small then the algorithm may not converge properly and there may be an error in particle pairing results. On the other hand, the CNN method is another interesting attempt with a concept of the minimization of Lyapunov energy function, but in order to get reasonable matching results, the energy function must be composed of four object functions representing the physical constraints of the flow. This complicates the computation process with an additional problem of the weight balance of the multiple object functions.

From such a background, the present authors have been trying to establish a new particle pairing strategy for stereoscopic particle images obtained from a two-camera arrangement. The point of their new strategy is the use of ACO based algorithms applied to the epipolar line nearest-neighbor analysis. The principle of the ACO algorithm was originally proposed by Dorigo et al. [19] to solve the traveling salesperson problem (TSP). This is a kind of algorithm for optimal solution problems and seems attractive for the particle tracking in the sense that the method uses a concept of group intelligence. In this regard, the ACO algorithm has already been applied by Takagi [20] and two of the present authors [21] with successful results for the time-differential particle images. Although the epipolar line particle pairing between spatio-differential particle images is not based on the same type of image disparity as in the time-differential images, the ACO algorithm can also be an effective particle pairing strategy for the former case, because the group intelligence principle of ACO could work well for minimizing the mismatch of the particle projection point and the relevant epipolar line. Bearing this in mind, in this research, an ACO algorithm has been applied to the epipolar constraint analysis in the stereoscopic particle pairing. The accuracy of the current spatial particle pairing results is examined by using the PIV standard images [22].

2. Ant colony optimization

2.1. Basic principle

Ant algorithms were inspired by the observation of real ant colonies. Ants are social insects that live in colonies and their behavior is directed more to the survival of the colony as a whole than to that of a single individual component of the colony. An important and interesting behavior of ant colonies is their foraging behavior, and, in particular, how ants can find shortest paths between food sources and their nest. The ant colony optimization (ACO) is an algorithm that imitates the behavior of a group of ants searching for food and bringing it back to their nest [19]. Their food collection is a co-operative work of the ants going on a scouting mission and those collecting foods. While walking from food sources to the nest and vice-versa, ants deposit on the ground a substance called pheromone, forming in this way a pheromone trail. The pheromone trail allows the ants to find their way back to the food source (or to the nest). Also, it can be used by other ants to find the location of the food sources found by their nest mates. Ants can smell pheromone and, when choosing their way, they tend to choose paths marked by strong pheromone concentrations. The routes on which the ants do not go often lose their pheromone by evaporation and are gradually abandoned. Only those routes which more ants follow survive. In this way, when more paths are available from the nest to a food source, a colony of ants is able to exploit the pheromone trails left by the individual ants to discover the shortest path from the nest to the food source and back while discarding longer routes.

Individual ants conduct themselves according to two simple rules: (1) they travel at a constant speed while marking their route with pheromone; (2) they make their way on the routes with stronger pheromone. However if the ants are viewed as a group, they also behave as if there were intelligence in the mass of ants. And this sort of group intelligence can be described as the essence of the ant colony optimization. In order to reproduce such behaviors (individuals as well as group behaviors) of ants in a real life ACO algorithm, at first, a number of agents imitating individual ants are prepared for work. These ant agents act independently in the space of the problem to be solved. Then they travel from different points in the space searching for the solution which they try to find out by combining two kinds of information. The first one is the short-sighted information obtained from direct views of the problem and the second one is the global information drawn from the group activities of ant agents, i.e., the pheromone amount.

The traveling salesman problem (TSP) is an example of a typical problem to which the ACO was applied [19]. Given a collection of cities and the cost of travel between each pair of them, the TSP is a