Ant Colony System with Extremal Dynamics for Point Matching and Pose Estimation

S. Meshoul and M. Batouche
Computer Vision Group, LIRE Laboratory
Computer Science Department,
Mentouri University of Constantine
e-mail : {meshoul, batouche}@wissal.dz

Abstract

For a point-based image registration method, point matching is a hard and a computationally intensive task to handle especially when issues of noisy and outlying data have to be considered. In this paper we cast the problem as a combinatorial optimization task and we describe a global optimization method to achieve robust point matching and pose estimation for image registration purpose. The basic idea is to use Ant Colony System (ACS) as a population based search strategy to evolve promising starting solutions i.e affine transformations. An appropriate local search inspired from extremal optimization is developed and embedded within the search strategy to refine the solutions found. Experimental results are very promising and show the ability of the method to cope with outliers and to achieve robust pose estimation.

1. Introduction

For many tasks in computer vision and its related areas, point matching and pose estimation contribute jointly to relate two sets of points in order to bring into registration two images. Image registration is the process that attempts to align two images of roughly the same scene for comparison purposes. Therefore the best transformation relating the two images according to the variations causing their misalignment has to be found. Methods reported in the literature since the early seventies to early nineties have been reviewed in [1] and a methodology for classifying them has been described. According to Brown's work, an image registration method is defined as a combination of four elements choices : the search strategy, the similarity metric, the search space and the feature space.

A feature-based image registration method requires reliable feature extraction and feature matching procedure to robustly estimate the best registering transformation parameters. In this paper, we are interested by point-based image registration and especially by point matching and pose estimation problem. The methods proposed in the literature to address this problem range from relaxation, tree pruning, clustering, to the recently investigated methods using neural networks, genetic algorithms and robust similarity measures [2,3]. Although it has been for a long time the focus of a considerable amount of research effort, some of its aspects still need deeper studies. Indeed, most of the methods which cast the problem as an energy minimization task focuses more on the definition of the cost function than on the optimization technique used. For the latter, mathematical techniques have been used like the gradient descent and Powell's method. A reliable initial guess is generally necessary to ensure the convergence to good quality solutions. Recently global optimization methods have aroused interest among researchers like in [4]. In this context, we propose the use of ant colony optimization approach to define a new search strategy for point-based image registration. It aims to evolve promising initial solutions which are refined by an appropriate local search inspired from extremal optimization.

2. Ant colony optimization meta-heuristic

Ant Colony Optimization (ACO) is a new paradigm proposed by Dorigo and colleagues [5] to solve difficult discrete combinatorial optimization problems like the traveling salesman and quadratic assignment problems. As the name suggests, ACO paradigm is inspired from the foraging behavior of real ants within a colony. This foraging behavior relies on cooperation and local stigmergic communication between ants. To find shortest paths from their nest to the food sources, real ants make use of a chemical substance called pheromone which is subject to evaporation. By analogy to real ants, ACO paradigm relies on the main following aspects : - artificial ant which is a simple agent whose task is to construct a

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solution to the problem at hand, - artificial pheromone trail which is a numeric information encoding the desirability of the solution components, - the heuristic function, which is problem specific, encodes the attractiveness of the solution components, - the probabilistic transition rule which allows to choose a component during the construction of a solution according to its desirability and its attractiveness, - the artificial pheromone updating policy which defines the way the pheromone trails is updated according to the quality of the constructed solution.

Ant system (AS) is the first ACO algorithm proposed [5,6]. During the last decade, many ACO algorithms have been developed and applied to a various number of Benchmark problems as well as to real world applications. Ant Colony System (ACS) [7-9] is one of these algorithms. ACO algorithms rely on the same algorithmic framework but they differ by the transition rule and the pheromone trail policy used.

3. Point matching as an energy minimization problem

The problem we address in this work may be formulated in this way. Given two sets of points $P_1=\{S_i \; i=1..n_1\}$ and $P_2=\{R_j \; j=1..n_2\}$ extracted from two images I_1 and I_2 using an appropriate point extraction procedure, we have to find the best affine transformation $A=(L,T)$ relating the two sets of points and corresponding to the global minimum of an energy function. For this purpose, we define a match-matrix $M=(m_{ij})$ representing the point-to-point correspondences as follows :

$$m_{ij} = \begin{cases} 1 & \text{if point } S_\mathrm{i} \text{ corresponds to point } R_\mathrm{j} \\ 0 & \text{otherwise} \end{cases}$$

To handle the problem of outliers i.e. points in one image that have not their correspondents in the other image, an extra row and an extra column called slacks are added to the match-matrix. A point is considered as an outlier when its corresponding slack element is set to 1. The mapping transformation is such that :

$$R_j = L\,S_i + T + \varepsilon_{ij}$$

where L is a linear transformation represented by a 2x2 matrix, T is a translation vector of dimension 2, and ε_{ij} is a residual term which represents some white noise. S_i and R_j are the matched points. The energy function to be minimized is defined as:

$$E(M,T,L) = E_1 + E_2$$

where

$$E_1 = \sum_{i=1}^{n_1}\sum_{j=1}^{n_2} m_{ij}\left(R_j - LS_i - T\right)^2$$

and

$$E_2 = \lambda\left(\sum_{i=1}^{n_1} m_{i(n_2+1)} + \sum_{j=1}^{n_2} m_{(n_1+1)j}\right) + g(L)$$

The term E_1 represents the sum of the squares of residuals ε_{ij}. The term E_2 is used to reinforce all correct matches while rejecting outliers and to control the bounds of the transformation parameters by mean of the term $g(L)$. Thus, the process consists of finding the match matrix M which provides the best mapping transformation through the minimization of the energy function $E(M,T,L)$. Obviously, this is a combinatorial optimization problem as the number of configurations to be checked grows exponentially with the number of points and the presence of outliers.

4. Ant colony system for point matching and pose estimation

The developed algorithm is inspired by work on ant colony system (ACS), a distributed algorithm for combinatorial optimization recently proposed in [7]. It is in fact, an iterative process which integrates both point matching and pose estimation. The first step in solving the problem described above is to decide about the representation scheme which allows the ants moves to be interpreted as a solution of the problem.

For our case, a problem solution is given by a match matrix from which the transformation parameters are estimated. Therefore, each solution component is viewed as a pair representing an element of the match matrix that is a pair or an outlier. Each artificial ant used has the task to construct a match matrix. The pheromone trail is represented by a matrix of dimension (n_1+1,n_2+1). The elements of this matrix τ_{ij} encode the desirability of the corresponding pairs. Therefore a slack element represents the amount of pheromone when considering the corresponding point as an outlier. The heuristic function should measure the score matching between two points. For this purpose, we make use of a correlation-based measure (linear correlation coefficient) to compute the correlation between intensity patterns within local neighborhoods around the considered points. The heuristic function values η_{ij} are computed once for all at the beginning of the process and stored in a matrix of dimension (n_1+1,n_2+1)

4.1. Algorithm description

To solve the problem, a colony of m artificial ants has been employed. Informally, the principal of our algorithm can be described in the following manner. Each artificial ant k builds a feasible solution by constructing a match matrix. This construction process is done step by step by selecting pairs using a stochastic and greedy transition rule, specific to ACS, called the pseudo-random rule. This mainly consists in applying the following probabilistic decision:

Given a value q randomly chosen with uniform distribution in [0,1] and q_0 a tunable parameter in [0,1]

If $\boldsymbol{q \le q_0}$ then

$$(\boldsymbol{S},\boldsymbol{R}) = \arg\max\left\{\left[\tau_{ij}(t)\right]\left[\eta_{ij}\right]^{\beta}\right\}$$

Otherwise, **when** $\boldsymbol{q > q_0}$

A pair (S, R) is chosen randomly according to the following probability distribution :

$$P_{SR}^{k}(t) = \begin{cases} \dfrac{\left[\tau_{SR}(t)\right]\left[\eta_{SR}\right]^{\beta}}{\sum\left[\tau_{ij}(t)\right]\left[\eta_{ij}\right]^{\beta}} & \text{if } S \notin Tabulist_k \text{ and } R \notin Tabulist_k \\ 0 & \text{otherwise} \end{cases}$$

where $\tau_{SR}(t)$ and η_{SR} are respectively the amount of pheromone at the time t and the heuristic function value corresponding to the pair (S,R). β is a parameter which weighs the relative importance of pheromone trail and the heuristic function. $Tabulist_k$ is the memory of ant k initially empty. The selected points are added to the tabulist.

Once the match matrix construction is achieved that is when all points were treated, the corresponding transformation parameters are estimated using a least of squares approximation. The solution is then evaluated by computing its corresponding energy function value E_k. At this time, local pheromone updating is performed. It is intended to diminish the pheromone trail on the used pairs in order to favor the exploration of new pairs (diversification). The pheromone updates is performed by applying the rule :

$$\tau_{SR}(t+1) = (1-\varphi)\tau_{SR}(t) + \varphi\tau_0$$

φ is a tunable parameter within [0,1], and τ_0 is a small positive constant value. When a cycle is completed that is when all artificial ants have constructed and evaluated their solutions and performed local pheromone updating, the ant that obtained the best solution from the beginning of the trial performs a global trail pheromone updating. This latter is intended to reward the matches belonging to the best solution. The best ant deposits an amount of pheromone which is a function of the cost of its solution :

$$\tau_{SR}(t+1) = (1-\rho)\tau_{SR}(t) + \rho\,\Delta\tau_{SR}(t)$$

where ρ is a parameter within [0,1] and $\Delta\tau_{SR}(t) = 1/E^{best}$. E^{best} is the minimum of $E_k(M,T,L)$ computed from the beginning of the trial. It is important to note that the trail update only applies to the matches of the global-best mapping. The objective of such an update is to favor the exploration of the neighborhood of good solutions more completely (intensification). The whole process is then repeated until a termination-criterion is reached (maximum number of iterations).

4.2. Extremal optimization as local search

In order to improve the performances of the previous algorithm from both speed and quality of the result point of views, we have developed an appropriate local search which takes into account the characteristics of the solution to be found. As explained above, a solution is represented by a match-matrix which may contain pairs of points representing matches, and outliers. Its quality is measured by the corresponding cost function value. Given a match-matrix, each match (S_i,R_j) used in the pose estimation process has some contribution with regard to the quality of the corresponding affine transformation A=(L,T). This contribution is evaluated by the corresponding residual ε_{ij} ($\varepsilon_{ij} = R_j - L\,S_i - T$). The less is the residual ε_{ij}, the better and more desirable is the match (S_i,R_j) for the current solution.

Therefrom, one way to improve the quality of a solution may be to exchange a point belonging to the worst match with an outlier, if any. The proposed local search heuristic is based on such local updating. It consists merely in replacing the undesirable matches (S, R) by choosing randomly an outlier in the current solution to exchange with S or R depending on the type of the outlier. In fact, such local search heuristic follows the spirit of τ-Extremal Optimization (τ-EO), a new heuristic introduced recently by Boettcher and Percus [10,11] inspired from Self-Organized Criticality (SOC), a concept describing complexity in physical systems. Therefrom, given a solution to be improved, all its matches are ranked according to their residual. The worst match is of rank 1, and the best match is of rank n. We select then a match to be exchanged with a randomly chosen outlier according to the probability distribution over the ranks k :

$$P(match_k) \propto k^{-\tau} \text{ with } k \in [1..n]$$

5. Experimental results

Both synthetic and real data have been used to assess the performance of the proposed approach by focusing on accuracy and convergence criteria. Preliminary experiments have been conducted in order to find suitable parameter settings. Good results have been obtained with the following values : $m = 15$ ants, $\beta = 2$, $\tau_0 = 0.001$, $\varphi = \rho = 0.1$, $q_0 = 0.7$ and $\lambda = 10$. In the local search procedure, the parameter τ was set to 2.0. Figure 1 shows the application of the method to aerial images. Control points have been extracted using Harris' detector [12].

The obtained results have shown that sub-pixel accuracy has been achieved. To have an insight into the behavior of the proposed method, convergence has been studied by monitoring the behavior of the cost function with and without local search. Excellent convergence is reached when applying ACS with local search. Furthermore, we have also observed that the results remain stable up to 30% of contamination by outliers.

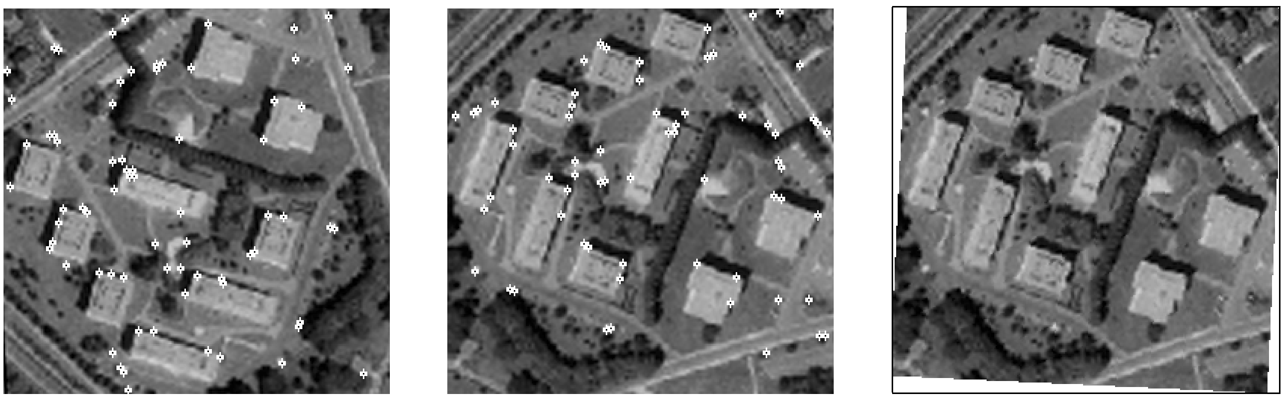

Figure 1. Image registration using ACS Algorithm : The sensed image (left) the reference image (middle) The transformed sensed image using the best transformation found (right)

6. Summary

A new search strategy for point-based image registration which integrates both point matching and pose estimation has been described. It is based on a probabilistic construction heuristic combined with a local search inspired from extremal optimization. In the former, a colony of cooperating agents has been employed to construct feasible solutions while with the latter, the solutions found are refined to improve their quality. Experimental results are very encouraging and demonstrate the feasibility of the method and its ability to cope with noise and outliers.

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