A novel technique based on ant colony optimization for image stitching

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Abstract

Image stitching is the process of combining multiple photographic images with overlapping fields of view to produce a panoramic or high-resolution image. Most approaches to image stitching require nearly exact overlaps between images and identical exposures to produce seamless results. In digital radiography oversized images have to be assembled from multiple exposures. As the patient may have moved in between subsequent exposures, an external feature is exposed together with the anatomy. The exposures typically have a very small overlap which complicates the registration. This review paper, discusses a fast and accurate technique using ant colony optimization for image stitching. Ant colony optimization not only save time but also gives the accuracy to stitch the image. With the help of this technique edges for land marking and features of different medical images (X-rays) can be found. Finding correlations between found landmarks to check the alignment between the images and RANSAC algorithm is used to eliminate the spurious feature points. Then finally stitch the images using blending technique.

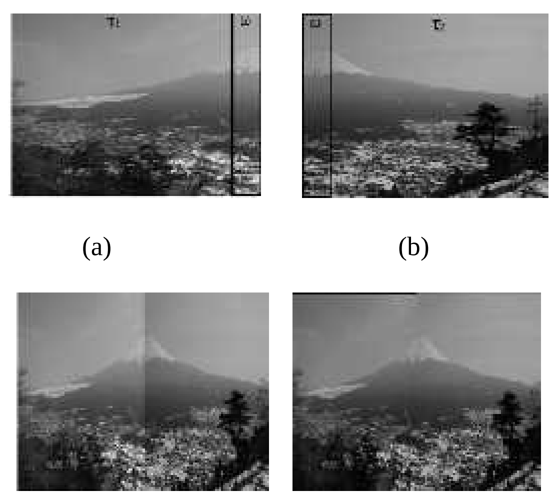
Keywords

Image Stitching, Ant colony optimization, feature extraction, feature matching, Correlation, RANSAC, Image blending

I. Introduction

Image stitching is the process that integrates two or more small images, which have some overlapped area, into a large-size image with a wild field of view. The goal of image stitching is to create wide angle and high resolution panorama image from various image sources [8]. Image stitching algorithms create the high resolution photo- mosaics used to produce today's digital maps and satellite photos and medical imaging. Commonly performed through the use of computer software, most approaches to image stitching require nearly exact overlaps between images and identical exposures to produce seamless results [11].

The aim of stitching is to produce a visually plausible mosaic with two desirable properties. First, the mosaic should be as similar as possible to the input images, both geometrically and photometrically. Second, the seam between the stitched images should be invisible. An example of image stitching is shown in Fig1. Two images I1, I2 capture different portions of the same scene, with an overlap region viewed in both images. The images should be stitched to generate a mosaic image I, where w is the overlap region [14].



(a) (b) (c) (d)

Fig.1 (a) Input image 1, (b) Input image 2, (c) Stitching of I1 and I2, (d) Stitching results (I)

We worked on medical images like X-rays for imaging long parts of the human body e.g. legs or spine. When imaging such parts in conventional screen-film technique; special cassettes and films of extended length are utilized. Migration to digital radiography limits the image size due to the sensitive area of flat-panel detectors. In digital radiography oversized images have to be assembled from multiple exposures. As the patient may have moved in between subsequent exposures, an external feature is exposed together with the anatomy. The exposures typically have a very small overlap which complicates the registration. In order to reproduce the behavior of conventional radiography a large image is assembled from multiple exposures with a small spatial overlap. This technique is commonly referred to as stitching. Due to the high rate of examinations it is necessary to reduce manual interaction of the operator to a minimum and automatically stitch radiographs [12]

Majority of the Stitching methods consists of the following steps [13]

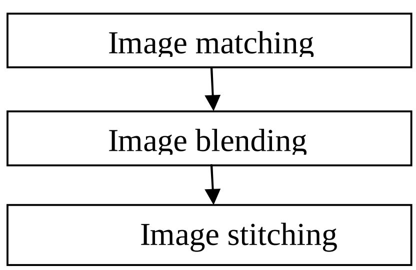


Fig. 2 Block diagram of image stitching

1. *Image matching* : It is used to find the motion relationship between several images and it directly relates to the success rate and speed of the total process
2. *Image blending*: It is used to eliminate the various illumination of the adjacent image or color does not consecutive caused by geometric correction or dynamic scene illumination
3. *Image stitching*: It integrates the several images into a high resolution image and produces seamless results

1. Ant colony Optimization

Ant colony optimization (ACO) is used to solve discrete combinatorial optimization problems [4]. The ACO was originally applied to solve the classical travelling salesman problem, where it was shown to be an effective tool in finding good solutions. The ACO has also been successfully applied to other optimization problems including data mining and telecommunications networks [1]. For other complex problems, such as the quadratic assignment problem, data clustering, image retrieval, graph coloring [6], Ant-based algorithms have been as well proposed to solve the problem of edge detection [5]. ACO is more suitable for image processing problems, such as segmentation, feature extraction, image matching and texture classification [6].

In the natural world, ants (initially) wander randomly, and upon finding food return to their colony while laying down pheromone trails. If other ants find such a path, they are likely not to keep travelling at random, but to instead follow the trail; returning and reinforcing it if they eventually find food [1]

Over time, however, the pheromone trail starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel down the path and back again, the more time the pheromones have to evaporate. A short path, by comparison, gets marched over more frequently, and thus the pheromone density becomes higher on shorter paths than longer ones. Pheromone evaporation also has the advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained [1]

Thus, when one ant finds a good (i.e., short) path from the colony to a food source, other ants are more likely to follow that path, and positive feedback eventually leads to all the ants' following a single path. The idea of the ant colony algorithm is to mimic this behavior with "simulated ants" walking around the graph representing the problem to solve.

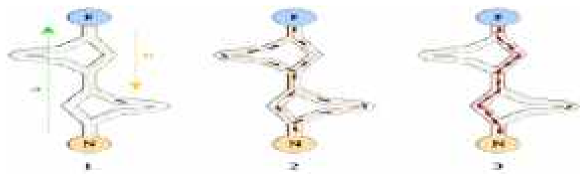


Fig. 3 Diagram showing positive feedback loop

The original idea comes from observing the exploitation of food resources among ants, in which ants' individually limited cognitive abilities have collectively been able to find the shortest path between a food source and the nest.

1. The first ant finds the food source (F), via any way (a), then returns to the nest (N), leaving behind a trail pheromone (b)
2. Ants indiscriminately follow four possible ways, but the strengthening of the runway makes it more attractive as the shortest route.
3. Ants take the shortest route; long portions of other ways lose their trail pheromones.

In a series of experiments on a colony of ants with a choice between two unequal length paths leading to a source of food, biologists have observed that ants tended to use the shortest route. A model explaining this behavior is as follows:

1. An ant (called "blitz") runs more or less at random around the colony.
2. If it discovers a food source, it returns more or less directly to the nest, leaving in its path a trail of pheromone.
3. These pheromones are attractive; nearby ants will be inclined to follow, more or less directly, the track.
4. Returning to the colony, these ants will strengthen the route.
5. If there are two routes to reach the same food source then, in a given amount of time, the shorter one will be traveled by more ants than the long route.
6. The short route will be increasingly enhanced, and therefore become more attractive.
7. The long route will eventually disappear because pheromones are volatile.
8. Eventually, all the ants have determined and therefore "chosen" the shortest route.

1.1 Feature selection based on ant colony optimization

Feature selection is an important step in many pattern classification problems [2]. The aim of feature selection is to remove irrelevant or redundant features while keeping the most informative ones [3]. Searching the feature subset space is another important aspect that has been widely investigated. This is reflected by the different search procedure methods. Among those, population-based optimization algorithms have attracted a lot of attention. Such methods attempt to achieve better solutions by utilizing knowledge from previous iterations. One of the population-based algorithms is the Ant Colony Optimization algorithm (ACO) [1]. The problem of feature selection has been widely investigating due to its importance to a number of disciplines such as pattern recognition and knowledge discovery. Feature selection allows the reduction of feature space, which is crucial in reducing the training time and improving the prediction accuracy. This is achieved by removing irrelevant, redundant, and noisy features (i.e., selecting the subset of features that can achieve the best performance in terms of accuracy and computational time) [2].

According to Blum and Langley [7, 2] the most existing feature selection algorithms consist of the following four components:

1. *Starting point in the feature space*: The search for feature subsets could start with (i) no features, (ii) all features, or (iii) random subset of features. In the first case, the search proceeds by adding features successively, while in the second case, features are successively removed. When starting with a random subset, features could be successively added/removed, or reproduced by a certain procedure.
2. *Search procedure:* Ideally, the best subset of features can be found by evaluating all the possible subsets, which is known as exhaustive search. However, this

becomes prohibitive as the number of features increases, where there are *2N* possible combinations for *N* features. Accordingly, several search procedures have been developed that are more practical to implement, but they are not guaranteed to find the optimal subset of features. These search procedures differ in their computational cost and the optimality of the subsets they find.

3. *Evaluation function:* An important component of any feature selection method is the evaluation of feature subsets. Evaluation functions measure how good a specific subset can be in discriminating between classes, and can be divided into two main groups: filters and wrappers. Filters operate independently of any learning algorithm, where undesirable features are filtered out of the data before learning begin. On the other hand, performance of classification algorithms is used to select features for wrapper methods [1, 3].

4. *Criterion (or stopping the search):* Feature selection methods must decide when to stop searching through the space of feature subsets. Some of the methods ask the user to predefine the number of selected features. Other methods are based on the evaluation function, like whether addition/deletion of any feature does not produce a better subset, or an optimal subset according to some evaluation strategy is obtained.

2. Co- relation method

In many image processing applications it is necessary to form a pixel-by-pixel comparison of two images of the same object field obtained from different sensors, or of two images of an object field taken from the same sensor at different times[9,10]. Thus, between these images there may be translational shifts, rotational differences, scale and perspective view differences. Re-mote Sensing Systems, Synthetic Aperture Radar Imaging, Computed Tomography using Magnetic Resonance Imaging, Image stitching in digital radiography, image mosaicing are some of the many applications in which image registration is required. In some applications the shifts and differences are detected and corrected off-line, while in others the acquired sequence of images has to be aligned in real time [10].

To form this comparison it is necessary to spatially register the images and thereby correct for relative translational shifts, magnification differences, and rotational shifts, as well as geometrical and intensity distortions of each image. Often it is possible to eliminate or minimize many of these sources of misregistration by proper static calibration and compensation of the image sensor; in some applications misregistration detection and subsequent correction must be performed dynamically for each pair of images [9].

A broad range of registration techniques have been developed for various types of data and problems. It is divided into two major classes, namely the techniques based on area correlation either in spatial or frequency domain, and the techniques based on matching properly chosen features or models of the images. The several techniques are compared according to criteria as accuracy, applicability and restrictions, level of automation and computational complexity [10].

3. RANSAC method

The RANdom SAmple Consensus (RANSAC) is an iterative method to estimate parameters of a mathematical model from a set of observed data which contains outliers. It is a non-deterministic algorithm in the sense that it produces a reasonable result only with a certain probability, with this probability increasing as more iterations are allowed.

The data consists of "inliers", i.e., data whose distribution can be explained by some set of model parameters, and "outliers" which are data that do not fit the model. In addition to this, the data can be subject to noise. The outliers can come, e.g., from extreme values of the noise or from erroneous measurements or incorrect hypotheses about the interpretation of data. RANSAC also assumes that, given a (usually small) set of inliers, there exists a procedure which can estimate the parameters of a model that optimally explains or fits this data.

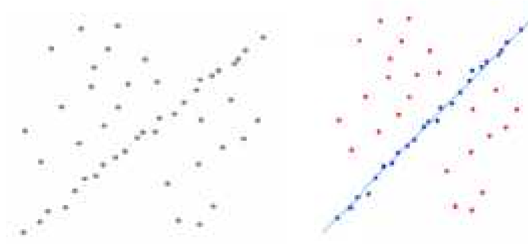
The input to the RANSAC algorithm is a set of observed data values, a parameterized model which can explain or be fitted to the observations, and some confidence parameters.

RANSAC achieves its goal by iteratively selecting a random subset of the original data. These data are hypothetical inliers and this hypothesis is then tested as follows:

1. A model is fitted to the hypothetical inliers, i.e. all free parameters of the model are reconstructed from the inliers.
2. All other data are then tested against the fitted model and, if a point fits well to the estimated model, also considered as a hypothetical inlier.
3. The estimated model is reasonably good if sufficiently many points have been classified as hypothetical inliers.
4. The model is re-estimated from all hypothetical inliers, because it has only been estimated from the initial set of hypothetical inliers
5. Finally, the model is evaluated by estimating the error of the inliers relative to the model

This procedure is repeated a fixed number of times, each time producing either a model which is rejected because too few points are classified as inliers or a refined model together with a corresponding error measure. In the latter case, we keep the refined model if its error is lower than the last saved model.

An advantage of RANSAC is its ability to do robust estimation of the model parameters, i.e., it can estimate the parameters with a high degree of accuracy even when a significant number of outliers are present in the data set.



(a) (b)

Fig.4 Show a simple application of the RANSAC algorithm on a 2-dimensional set of data, (a) is a visual representation of a data set containing both inliers and outliers, (b) shows all of the outliers in red, and shows inliers in blue. The blue line is the result of the work done by RANSAC.

II. Future Perspectives

Image stitching process can be improved by using a combination of different methods like ACO (Ant Colony Optimization), Correlation and RANSAC (RANdom SAmple Consensus). ACO can be applied for finding the edges for land marking and features of different medical images. Finding correlation between found landmarks to check the alignment between the images. RANSAC is applied for eliminating the unnecessary feature points. Finally stitch the images using image blending.

III. Conclusion

In this paper, we propose a novel technique based on Ant colony optimization not only save time but also gives the accuracy to stitch the images.

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