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On energy hole and coverage hole avoidance in underwater wireless sensor network

[1]Mr. S.Sambasivam MCA.,M.Phil., Associate Professor,
[2]Ms N. Karthiga Final M.C.A,
Department of MCA, Nandha Engineering College (Autonomous), Erode-52.

up2111@gmail.cE-mail id: karthi.tom

Abstract**—*Due to limited battery capacity of sensor nodes, minimization of energy consumption is a potential research area in Underwater Wireless Sensor Networks (UWSNs). However, energy hole and coverage hole creation leads performance degradation of UWSNs in terms of network lifetime and throughput. It address the energy hole creation issue in depth based routing techniques, and devise a technique to overcome the deficiencies in existing techniques. Besides addressing the energy hole issue, proposition of coverage hole repair technique is also part of this research work. In areas of dense deployment, sensing ranges of nodes redundantly overlap. Coverage-Aware Sensor Automation (CASA) protocol is proposed to realize an automated smart monitoring network. Two centralized algorithms are included in the CASA protocol suite: Enhanced Virtual Forces Algorithm with Boundary forces (EVFA-B) and Sensor Self-Organizing Algorithm (SSOA). Unlike most previous works that tackle the deployment problem only partially, we intend to address the problem from both global deployment (EVFA-B) and local repairing (SSOA) perspectives.***

I INTRODUCTION

Images with large local geometric differences have been registered by a multiresolution method. Such methods uniformly reduce resolution of images until the images are small and simple enough to be registered by a rigid, similarity, or affine transformation. These multiresolution methods use the registration result at one resolution to guide registration at a finer resolution. Registration parameters obtained at a resolution are refined by gradually increasing resolution and optimizing a measure of match between the images.

Progressive subdivision algorithm is developed. Using the correspondences at a coarse resolution, the images at one level higher resolution are subdivided into corresponding regions through Voronoi subdivision. The subdivision process is repeated from low to high resolution until images at the highest resolution are subdivided into small enough corresponding regions, each suitable for registration by affine transformation. Correspondence is then established between points within corresponding regions by a RANSAC algorithm with affine transformation.

The idea of piecewise image registration is not new. They considered a scene a combination of rigid objects and registered regions corresponding to an object in the images by first determining correspondence between points in images using image features, clustering the correspondences into regions, and determining the fundamental matrix of a stereo camera setup that could have captured the images using a rigid transformation in a RANSAC algorithm. Knowledge about the fundamental matrix and the correspondences is used to approximate the geometry of the scene by a piecewise continuous surface.

They achieve piecewise registration without initial feature based matching and without the use of fundamental matrix. By keeping the correspondence process local through image subdivision and in a hierarchical manner, an efficient and robust correspondence process is developed. This correspondence process is then used to register images of 3-D scenes captured from different views.

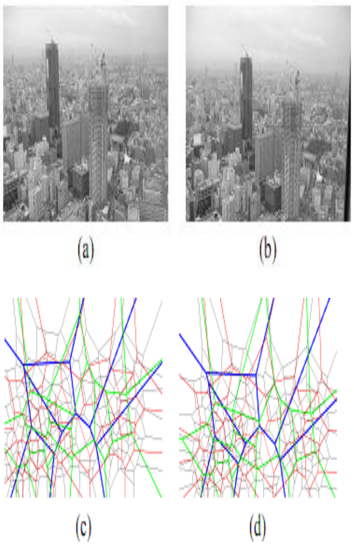
Then resolution of images is progressively increased allowing new region to merge. By keeping track of point correspondences, they establish correspondence between newly merged regions without iterations and cooperative processes.

An exception is the Voronoi Laguerre diagram, which is also called the power diagram. In this diagram the Voronoi edges are portions of straight lines, and they are perpendicular to the line segments connecting the centers of the associated two generating circles.

The Voronoi Laguerre diagram, also called the power diagram, is one of the important generalizations of the Voronoi diagram in the plane, in which the generating points are generalized to circles and the distance is generalized to the Laguerre distance. The Laguerre distance from a point to a circle on the sphere is defined as the geodesic length of the tangent line segment from the point to the circle. This distance defines a new variant of the Voronoi diagram on the sphere, and it inherits many characteristics from the Voronoi Laguerre diagram in the plane.

II PROBLEM DESCRIPTION

The problem to be solved is as follows: Given two images of a 3-D scene taken from different views, it would like to find the correspondence between as many points in the images as possible so that the images can be accurately registered. The images may be very large and have local geometric differences. It is assumed that the images are captured either by the same camera or by cameras with similar optical characteristics. An example of the kind of images to be registered is given in Fig. 1. To solve the problem, a new method is developed which is a feature-based one and uses points with more similar pixels in the selected area as features. Feature points as referred as control points.


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

a.

MAIN OBJECTIVES

- To subdivide large images into small corresponding regions and by registering small regions, register the images in a piecewise manner.
- Through Image subdivision, reduce the geometric difference between regions that are registered and simplify the correspondence process.
- To take content of the image pixels into consideration during VorLag subdivision.
- To reduce registration error along depth discontinuities.
- To take same image with different resolution for VorLag subdivision and accomplish the registration.
- To segment the image in which images with different density in different areas are used to fix the mid points.

SPECIFIC OBJECTIVES

- To construct the Voronoi polygon by selecting mid points based on image content.
- To construct the VorLag polygon by selecting two points based on density of pixels in image content.
- To compare constructed polygon results from the same image taken with different resolution.
- To adapt different block size and shape based on the local image details and geometric difference between the images.

III LITERATURE SURVEY

In the paper “Patch Match: A Randomized Correspondence Algorithm for Structural Image Editing” [1] the authors C. Barnes, E. Shecht man, A. Finkelstein, and D. B Goldman, were stated that paper presents interactive image editing tools using a new randomized algorithm for quickly finding approximate nearest neighbor matches between image patches. Previous research in graphics and vision has leveraged such nearest-neighbor searches to provide a variety of high-level digital image editing tools.

However, the cost of computing a field of such matches for an entire image has eluded previous efforts to provide interactive performance. The algorithm offers substantial performance improvements over the previous state of the, enabling its use in interactive editing tools. The key insights driving the algorithm are that some good patch matches can be found via random sampling, and that natural coherence in the imagery allows to propagate such matches quickly to surrounding areas.

They offer theoretical analysis of the convergence properties of the algorithm, as well as empirical and practical evidence for its high quality and performance. This one simple algorithm forms the basis for a variety of tools image retargeting, completion and reshuffling that can be used together in the context of a high-level image editing application.

Finally, they proposed additional intuitive constraints on the synthesis process that offer the user a level of control unavailable in previous methods.

As digital and computational photography have matured, researchers have developed methods for high-level editing of digital photographs and video to meet a set of desired goals. For example, recent algorithms for image retargeting allow images to be resized to a new aspect ratio – the computer automatically produces a good likeness of the contents of the original image but with new dimensions [Rubinstein et al. 2008 [2]; Wang et al. 2008 [3]].

Other algorithms for image completion let a user simply erase an unwanted portion of an image, and the computer automatically synthesizes a fill region that plausibly matches the remainder of the image [Criminisi et al. 2003 [4]; Komodakis and Tziritas 2007 [5]]. Image reshuffling algorithms make it possible to grab portions of the image and move them around the computer automatically synthesizes the remainder of the image so as to resemble the original while respecting the moved regions [Simakov et al. 2008 [6]; Cho et al. 2008 [7]].

In each of these scenarios, user interaction is essential, for several reasons: First, these algorithms sometimes require user intervention to obtain the best results. Retargeting algorithms, for example, sometimes provide user controls to specify that one or more regions (e.g., faces) should be left relatively unaltered.

Likewise, the best completion algorithms offer tools to guide the result by providing hints for the computer [Sun et al. 2005 [8]]. These methods provide such controls because the user is attempting to optimize a set of goals that are known to him and not to the computer. Second, the user often cannot even articulate these goals a priori. The artistic process of creating the desired image demands the use of trial and error, as the user seeks to optimize the result with respect to personal criteria specific to the image under consideration.

The role of interactivity in the artistic process implies two properties for the ideal image editing framework: (1) the toolset must provide the flexibility to perform a wide variety of seamless editing operations for users to explore their ideas; and (2) the performance of these tools must be fast enough that the user quickly sees intermediate results in the process of trial and error.

Most high level editing approaches meet only one of these criteria. For example, one family of algorithms known loosely as non-parametric patch sampling has been shown to perform a range of editing tasks while meeting the first criterion – flexibility [Hertzmann et al. 2001 [9]; Wexler et al. 2007 [10] ; Simakov et al. 2008 [6]]. These methods are based on small (e.g. 7x7) densely sampled patches at multiple scales, and are able to synthesize both texture and complex image structures that qualitatively resemble the input imagery.

Because of their ability to preserve structures,theycall this class of techniques structural image editing. Unfortunately, until now these methods have failed the second criterion – they are far too slow for interactive use on all but the smallest images. However, in this papertheywill describe an algorithm that accelerates such methods by at least an order of magnitude, making it possible to apply them in an interactive structural image editing framework.

To understand this algorithm,theymust consider the common components of these methods: The core element of nonparametric patch sampling methods is a repeated search of all patches in one image region for the most similar patch in another image region. In other words, given images or regions A and B, find for every patch in A the nearest neighbor in B under a patch distance metric.

They call this mapping the Nearest-Neighbor Field (NNF), illustrated schematically in the inset figure. Approaching this problem with a brute force search is expensive – O(mM2) for image regions and patches of size M and m pixels, respectively. Even using acceleration methods such as approximate nearest neighbors [Mount and Arya 1997 [7]] and dimensionality reduction, this search step remains the bottleneck of nonparametric patch sampling methods, preventing them from attaining interactive speeds.

Furthermore, these tree-based acceleration structures use memory in the order of O(M) or higher with relatively large constants, limiting their application for high resolution imagery. To efficiently compute approximate nearest-neighbor fields their new algorithm relies on three key observations about the problem: Dimensionality of offset space.

First, although the dimensionality of the patch space is large (m dimensions), it is sparsely populated (O(M) patches). Many previous methods have accelerated the nearest neighbor search by attacking the dimensionality of the patch space using tree structures (e.g., kd-tree, which can search in O(mMlogM) time) and dimensionality reduction methods (e.g., PCA).

In contrast, the algorithm searches in the 2-D space of possible patch offsets, achieving greater speed and memory efficiency. Second, the usual independent search for each pixel ignores the natural structure in images. In patch-sampling synthesis algorithms, the output typically contains large contiguous chunks of data from the input (as observed by Ashikhmin, 2001 [12]). Thus they can improve efficiency by performing searches for adjacent pixels in an interdependent manner.

Finally, whereas any one random choice of patch assignment is very unlikely to be a good guess, some nontrivial fraction of a large field of random assignments will likely be good guesses. As this field grows larger, the chance that no patch will have a correct offset becomes vanishingly small. Based on these three observations they offer a randomized algorithm for computing approximate NNFs using incremental updates.

The algorithm begins with an initial guess, which may be derived from prior information or may simply be a random field. The iterative process consists of two phases: propagation, in which coherence is used to disseminate good solutions to adjacent pixels in the field; and random search, in which the current offset vector is perturbed by multiple scales of random offsets.

They show both theoretically and empirically that the algorithm has good convergence properties for tested imagery up to 2MP, and the CPU implementation shows speedups of 20-100 times versus kd-trees with PCA. Moreover, they propose a GPU implementation that is roughly 7 times faster than the CPU version for similar image sizes.

The algorithm requires very little extra memory beyond the original image, unlike previous algorithms that build auxiliary data structures to accelerate the search. Using typical settings of the algorithm's parameters, the runtime is O(m MlogM) and the memory usage is O(M). Although this is the same asymptotic time and memory as the most efficient tree-based acceleration techniques, the leading constants are substantially smaller.

In the paper "Piecewise Image Registration in the Presence of Multiple Large Motions" [13] the authors P. Bhat, K. C. Zheng, N. Snavely, A. Agarwala, M. Agrawala, M. F.Cohen, and B. Curless were stated that they present a technique for computing a dense pixel correspondence between two images of a scene containing multiple large, rigid motions. They model each motion with either a homography (for planar objects) or a fundamental matrix.

The various motions in the scene are first extracted by clustering an initial sparse set of correspondences between feature points; then perform a multi-label graph cut optimization which assigns each pixel to an independent motion and computes its disparity with respect to that motion. They demonstrate the technique on several example scenes and compare the results with previous approaches.

Many real-world scenes contain multiple objects that undergo independent motions. Two photographs of such a scene taken at different moments of time and different viewpoints will contain motions much larger than most optical flow techniques can handle.

They consider the problem of estimating a dense correspondence between two such perspective views of a scene containing multiple, independent objects that undergo large, rigid motions. The algorithm computes this correspondence in a two two stage process. First, each independent motion is discovered by randomly sampling a set of sparse feature matches; second, each pixel in the reference view is assigned to a motion by optimizing a Markov random field formulation using graph cuts [14].

The two-stage process is very similar to the work of Wills et al. [15]; while they model motions using homographies, they model motions with both homographies and fundamental matrices. The advantage of using fundamental matrices is that the motion of an entire, rigid 3D object can be modeled with a single fundamental matrix.

Homographies, on the other hand, can only model the motion of 3D planes and thus multiple homographies are required to describe the motion of a typical 3D object. In addition, the approach can recover information about the 3D shape of independently moving objects. The disadvantage of using fundamental matrices is that, unlike other motion models (such as affine or planar perspective transformations) which explicitly provide a point to point correspondence, a fundamental matrix only describes the motion of each pixel up to an epipolar line.

Thus, to compute a dense pixel correspondence using fundamental matrices as a motion model, they need to both assign each pixel to a motion and choose a translation along that pixel's epipolar line to obtain a complete point-to-point correspondance. They use the term disparity to refer to this translation because the work bears a strong resemblance to estimating disparities for two-view stereo [16].

However, they handle multiple motions by allowing each pixel to choose a disparity along one of multiple epipolar lines. To handle planar objects, they also allow motions to be modeled with homographies and use a model selection heuristic to choose the appropriate motion model.

The main contribution of the work is to show that dense correspondence can be computed for scenes containing multiple large, rigid motions by assigning both a fundamental matrix and disparity to each pixel using Markov random field optimization. Since this optimization space is larger than both the work of Wills et al. [15] and graph cut-based stereo algorithms [17], they also show that a solution can be computed efficiently by limiting the range of possible disparities using a good initialization technique and hierarchical estimation.

To demonstrate the success of the approach they show their dense correspondence results and compare them to results computed using only homographies as a motion model. Finally, they demonstrate that they can reconstruct the 3D shape of individual objects in the scene by using the per-pixel disparities recovered by their approach.

In the paper “A new point matching algorithm for non-rigid Registration” [18] the authors H. Chui and A. Rangarajan were described that Feature-based methods for non-rigid registration frequently encounter the correspondence problem. Regardless of whether points, lines, curves or surface parameterizations are used, feature-based non-rigid matching requires to automatically solve for correspondences between two sets of features.

In addition, there could be many features in either set that have no counterparts in the other. This outlier rejection problem further complicates an already difficult correspondence problem. They formulate feature-based non-rigid registration as a non-rigid point matching problem. After a careful review of the problem and an in-depth examination of two types of methods previously designed for rigid robust point matching (RPM), they propose a new general framework for non-rigid point matching.

They consider it a general framework because it does not depend on any particular form of spatial mapping. They have also developed an algorithm the TPS-RPM algorithm with the thin-plate spline (TPS) as the parameterization of the non-rigid spatial mapping and the soft assign for the correspondence. The performance of the TPS-RPM algorithm is demonstrated and validated in a series of carefully designed synthetic experiments.

In each of these experiments, an empirical comparison with the popular iterated closest point (ICP) algorithm is also provided. Finally, they apply the algorithm to the problem of non-rigid registration of cortical anatomical structures which is required in brain mapping. While these results are somewhat preliminary, they clearly demonstrate the applicability of their approach to real world tasks involving feature-based non-rigid registration.

Feature-based registration problems frequently arise in the domains of computer vision and medical imaging. With the salient structures in two images represented as compact geometrical entities (e.g. points, curves, surfaces), the registration problem is to find the optimum or a good sub-optimal spatial transformation/mapping between the two sets of features.

The point feature, represented by feature location is the simplest form of feature. It often serves as the basis upon which other more sophisticated representations (such as curves, surfaces) can be built. In this sense, it can also be regarded as the most fundamental of all features. However, feature-based registration using point features alone can be quite difficult.

One common factor is the noise arising from the processes of image acquisition and feature extraction. The presence of noise means that the resulting feature points cannot be exactly matched. Another factor is the existence of outliers many point features may exist in one point-set that have no corresponding points (homologies) in the other and hence need to be rejected during the matching process.

Finally, the geometric transformations may need to incorporate high dimensional non-rigid mappings in order to account for deformations of the point-sets. Consequently, a general point feature registration algorithm needs to address all these issues. It should be able to solve for the correspondences between two point-sets, reject outliers and determine a good non-rigid transformation that can map one point-set onto the other.

The need for non-rigid registration occurs in many real world applications. Tasks like template matching for hand-written characters in OCR, generating smoothly interpolated intermediate frames between the key frames in cartoon animation, tracking human body motion in motion tracking, recovering dynamic motion of the heart in cardiac image analysis and registering human brain MRI images in brain mapping, all involve finding the optimal transformation between closely related but different objects or shapes.

It is such a commonly occurring problem that many methods have been proposed to attack various aspects of the problem. However, because of the great complexity introduced by the high dimensionality of the non-rigid mappings, all existing methods usually simplify the problem to make it more tractable. For example, the mappings can be approximated by articulated rigid mappings instead of being fully non-rigid.

These simplifications may alleviate the difficulty of the matching problem, but they are not always valid. The non-rigid point matching problem, in this sense, still remains unsolved. Motivated by these observations,they feel that there is a need for a new point matching algorithm that can solve for non-rigid mappings as well as the correspondences in the presence of noise and outliers.

The approach to non-rigid point matching closely follows earlier work on joint estimation of pose and correspondence using the soft assign and deterministic annealing (Gold et al., 1998 [20]; Rangarajan et al., 1997 [21]; Chui et al., 1999 [22]). This work was developed within an optimization framework and resulted in a robust point matching (RPM) algorithm which was restricted to using piece wise mappings.

In the paper “Optimal Randomized RANSAC” [25] the authors O. Chum and J. Matas were stated that a randomized model verification strategy for RANSAC is presented. The proposed method finds, like RANSAC, a solution that is optimal with user-specified probability. The solution is found in time that is close to the shortest possible and superior to any deterministic verification strategy.

A provably fastest model verification strategy is designed for the (theoretical) situation when the contamination of data by outliers is known. In this case, the algorithm is the fastest possible (on the average) of all randomized RANSAC algorithms guaranteeing a confidence in the solution. The derivation of the optimality property is based on Wald’s theory of sequential decision making, in particular, a modified sequential probability ratio test (SPRT). Next, the R-RANSAC with SPRT algorithm is introduced.

The RANSAC algorithm proceeds as follows: Repeatedly, subsets of the input data (for example, a set of tentative correspondences) are randomly selected (with replacement), and model parameters fitting these subsets are computed. In the second step, the quality of the parameters is evaluated on the input data. Different cost functions have been proposed [33], the standard being the number of data points (inliers) consistent with the model. The process is terminated when the probability of finding a better model becomes lower than a user-specified probability 0.

The confidence in the solution holds for all levels of contamination of the input data, that is, for any number of outliers within the input data. The speed of standard RANSAC depends on two factors: The number of random samples and the number N of the input data points. In all common settings where RANSAC is applied incorrect with arbitrary parameters originating from contaminated samples. Such models are consistent with only a small number of the data points.

They showed how this property could be exploited to increase the speed of RANSAC. The algorithm, called R-RANSAC, reduces the time needed for the model evaluation step by introducing a two-stage procedure. First, a statistical test is performed on d randomly selected data points

Evaluation of the remaining data points is carried out only if the first d data points are inliers. The speed up of R-RANSAC depends on the probabilities of the two types of errors committed in the pretest, the rejection of an uncontaminated model and the acceptance of a contaminated model.

IV CONCLUTION

A point location data structure can be built on top of the Voronoi diagram in order to answer nearest neighbor queries, where one wants to find the object that is closest to a given query point. Nearest neighbor queries have numerous applications. For example, one might want to find the nearest hospital or the most similar object in a database. A large application is vector quantization, commonly used in data compression.

Vorlag diagrams together with farthest-point Voronoi diagrams are used for efficient algorithms to compute the roundness of a set of points. The Voronoi approach is also put to good use in the evaluation of circularity / roundness while assesing the dataset from a Coordinate-measuring machine. In networking, Voronoi diagrams can be used in derivations of the capacity of a wireless network. In ecology, Voronoi diagrams are used to study the growth patterns of forests and forest canopies, and may also be helpful in developing predictive models for forest fires.

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