Object Localization Using Putative Point Matching in Cluttered Scene

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***Abstract-* in practice, the scene is often contaminated by clutters, making the point set matching problem more complicated. In this paper, we focus on how to locate a deformable shape in cluttered scenes under the no rigid point set matching framework. The shape May undergo arbitrary translational and rotational changes, and It may be no rigidly deformed and corrupted by clutters. To address the problem of rotation invariant no rigid point set matching, they proposed two methods for shape representation. The shape context (SC) feature descriptor was used and we constructed graphs on point sets where edges are used to determine the orientations of SCs. This enables the proposed methods rotation invariant. The goal of this project is to automatically detect and recognize some objects in an image by using a multi-agents architecture. A knowledge database is thus necessary and should contain an invariant description of known objects for the desired application. An agent processes an area of the image, its goal is to detect an object and check if this object belongs to the knowledge database. Here in this paper presents an algorithm for detecting a specific object based on finding point correspondences between the reference and the target image. It can detect objects despite a scale change or in-plane rotation. It is also robust to small amount of out-of-plane rotation**.

Index Terms—**Point matching, object, object detection, etc**

I. INTRODUCTION

In many applications of computer vision, pattern recognition and medical image analysis, one common procedure is to match two or more point sets, and non rigid point set matching is particularly difficult because the possible non rigid deformation of the model shape is numerous. In practice, the scene is often contaminated by clutters, making the point Set matching problem more complicated. In this paper, we focus on how to locate a deformable shape in cluttered scenes under the no rigid point set matching framework. The shape may undergo arbitrary translational and rotational changes, and it may be no rigidly deformed and corrupted by clutters.

When only point correspondence is concerned, point set matching can be formulated as a graph matching problem. State-of-the-art graph matching methods include graduated assignment, spectral methods and semi definite relaxation. Theory of dual decomposition was used to combine several optimization techniques to solve the graph matching problem in. Point set matching was formulated as an embedding problem. Where the to-be-registered point sets were embedded in the same Euclidean space by constructing a graph on them. The edges within individual point set were constructed based on spatial arrangement and the edges between different point sets were constructed based on feature similarity. The embedding was then implemented by solving an Eigen-value problem. In, the geometric neighborhood (i.e., graph) of point correspondences was represented as the categorical graph product of two point sets' spatial graphs. The graph Palladian was then used to regularize point correspondence during optimization. In, point set matching was formulated as the matching of neighborhood graphs (there is an edge between two points if they are neighbors') of two point sets. Relaxation labeling was used for optimization. This method exhibits good robustness to non rigid deformation and positional noise, but it is not robust to outliers. Besides, to enable rotation invariance, it requires that the two points sets 'mass centres should correspond to each other. For problems involving missing or erroneous structures, this requirement is difficult to satisfy. Our proposed methods can be interpreted as graph matching approaches as well, but they do not require that two point sets' mass centres must correspond to each other. Related work

II. RELATED WORK

As explained, the two variables, the transformation and the correspondence, in point matching problem are closely related. Once one variable is known, solution for the other is mostly straight forward. Consequently, if either variable can be independently determined, the matching problem can be considered solved. There are methods in the literature that are designed to take this kind of independent approach — namely, solve for one of the variables alone without even introducing the other. From our perspective, the intimate prior relationship between the two variables has been used, resulting in one variable dropping out of the formulation.

Other methods utilize this close relationship in a different way by treating point matching as a joint problem with both variables. With both variables in the picture, a simple alternating update process can then be implemented in the following manner: in phase one, one variable is held fixed and the other estimated and in phase two, the preceding sequence is reversed. During the alternation, each variable improved the other. The resulting algorithm is simple and usually yields good results provided the algorithm converge quickly. Thus all point matching algorithms can be characterized by examining the way they handle the two variables. In so far as a method attempts to solve either the correspondence or the transformation alone, it can be regarded as a independent estimation approach. On the contrary, if a method tries to find the solution for both variables, usually viaan alternating update scheme, it can be regarded as a joint estimation approach. We use this distinction to orient our description of previous research.

Independent Methods that Solve Only For the Transformation

Typically, these methods are designed for the point matching problem when only rigid transformations are involved. A search in the parameter space of rigid mappings is considered feasible due to the low dimensionality of the mapping. In 2D, a rigid/affine transformation has six parameters; and in the case of 3D, nine parameters are involved. Moment-of-inertia analysis [1] is a classical technique that attempts to solve for the transformation without introducing the notion of correspondence. Originated in physics, the idea is to find the centre of mass and the principa laxis of the data and use them to align the point-sets. The center of mass provides us with the information about the global location of the data and the principal axis with the information of global orientation. While the former can be used to estimate the translation component of the transformation, the later aids in the estimation of the rotation. This method is simple and but usually only provides a rough alignment.
A more sophisticated technique is the Hugh Transform [2,3]. The transformation parameter space is divided into small bins, where each bin represent a certain configuration of transformation parameters. The points are allowed to vote for all the bins and the bin which get the most votes is chosen. The answer typically rejects the “tyranny of the majority.” The voting procedure tolerates a reasonable amount of noise and outliers.
There are numerous other methods such as tree searches [4,8], the Hausdorff Distance[5], Geometric Hashing [12,21] and the alignment method [6] as well.

All these methods work well only for rigid transformations. When it comes to non-rigid mappings, the huge number of the transformation parameters (often proportional to the size of the dataset) usually renders these methods ineffective.

We suspect that this is the main reason for the relative dearth of literature in non-rigid point matching despite the long history of the problem for rigid, affine and projective transformations [8-14].

Independent Methods that Solve Only For the Correspondence

A different approach to the problem is to focus on the correspondence alone. For most problem formulations, it is usually necessary to search over all possible correspondences to guarantee optimality which is infeasible for even moderate problem sizes. Certain measures have to be taken to prune the search space. This is normally achieved by adding additional information into the correspondence estimation process. The extra information typically provides further constraints which cut down the search space. To this end, three different types of additional information can be used.

Use Higher Level Feature Structures

The first type of methods, typically referred to as dense feature-based methods, try to organize the feature points intohigher level feature structures such as line segments, lines, curves or surfaces through object parameterization [16,20,21]. In other words, after the feature segments are extracted, they are grouped together so that matching can be performed at the higher curve or surface level. Furthermore, the curves and/or surfaces are usually smooth which helps the matching process. Grouping is done using a curve/surface fitting step. Very often, a common parameterized coordinate frame (e.g. curve arc length) is used in this step to add local context (e.g. ordering) information. With the additional information acting as a constraint, the difficulty of searching through the high dimensional correspondence space is largely all eviated. Most of the curve matching and surface matching methods basically belong to this type. There is a huge amount of literature in the former two Felds, we only cited a few representative ones here.The relative advantages and disadvantages of this type of methods can be clearly seen in the curve matching case [17-19]. With the extra curve ordering information available, the correspondence space is drastically reduced making the correspondence problem much easier. Standard optimization approaches such as dynamic programming can then be used to find the best correspondence.
However, the requirement of such extra information imposes limitations on these methods. First, an additional curve fitting step is a prerequisite which normally requires good feature extractions. Both feature extraction and curvefitting can be difficult when the data is noisy or when the shapes involved are complex. Second, most of these methodsrely heavily on shape measures such as curvature to evaluate the similarity between curve segments. These measurescan only be reliably defined for curves with good geometrical properties (e.g. smoothness and continuity). For thisreason, these methods have difficulty matching curves that are broken (not continuous) or jagged (not smooth). Furthermore, most of these methods do not handle multiple curves or partially matched curves.

Use Local/Global Shape Attributes

The second type of methods work with more sparsely distributed point-sets. Shape attributes based on either local or global context are defined in these methods. The attributes are then used to determine the correspondence.
Following [20], the modal matching approach in [25] uses a mass and stiffness matrix that is built up from the Gaussian of the distances between any point feature in one set and the other. The eigenvectors of such matrices are ordered according their eigen values and are called mode shape vectors. The correspondence is computed by comparing each point’s relative participation in the Eigen-modes. The basic idea is that while a point-set of a certain shape is non-rigidly deforming, different points at different locations

should have systematically different ways of movement. Such differences are used to distinguish the points and determine their correspondences.

Robust point matching (RPM) was introduced by Gold et al. [10] The method performs registration using deterministic annealing and soft assignment of correspondences between point sets. Whereas in ICP the correspondence generated by the nearest-neighbour heuristic is binary, RPM uses a soft correspondence where the correspondence between any two points can be anywhere from 0 to 1, although it ultimately converges to either 0 or The correspondences found in RPM is always one-to-one, which is not always the case in ICP.

III.PROPOSED WORK

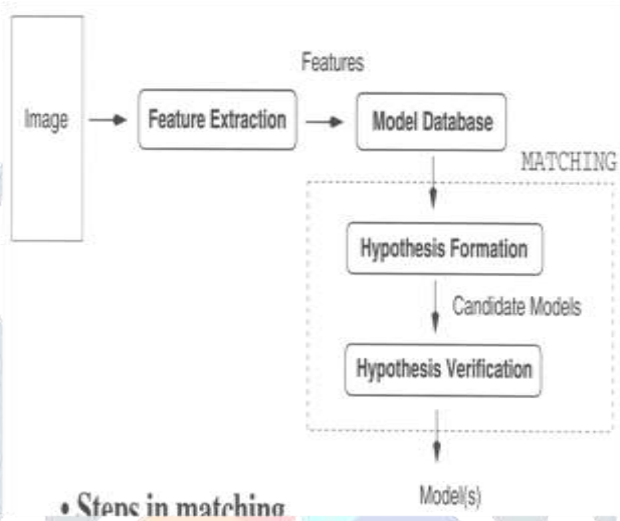

Fig.1:Object Recognition System

An object recognition system must have the following components to perform the task:

- Model database (also called modelbase)
- Feature detector
- Hypothesizer
- Hypothesis verifier

A block diagram showing interactions and information flow among different components of the system .

A.The model database

The model database contains all the models known to the system. The information in the model database depends on the approach used for the recognition. It can vary from a qualitative or functional description to precise geometric surface information. In many cases, the models of objects are abstract feature vectors, as discussed later in this section. A feature is some attribute of the object that is considered important in describing and recognizing the object in relation to other objects. Size, color, and shape are some commonly used features.

The feature detector applies operators to images and identifies locations of features that help in forming object hypotheses.

Feature-model matching

How can features in images be matched to models in the database? In most object recognition tasks, there are many features and numerous objects.

Hypotheses formation

How can a set of likely objects based on the feature matching be selected, and how can probabilities be assigned to each possible object? The hypothesis formation step is basically a heuristic to reduce the size of the search space. This step uses knowledge of the application domain to assign some kind of probability or confidence measure to different objects in the domain. This measure reflects the likelihood of the presence of objects based on the detected features.

Object verification

How can object models be used to select the most likely object from the set of probable objects in a given image? The presence of each likely object can be verified by using their models. One must examine each plausible hypothesis to verify the presence of the object or ignore it. If the models are geometric, it is easy to precisely verify objects using camera location and other scene parameters. In other cases, it may not be possible to verify a

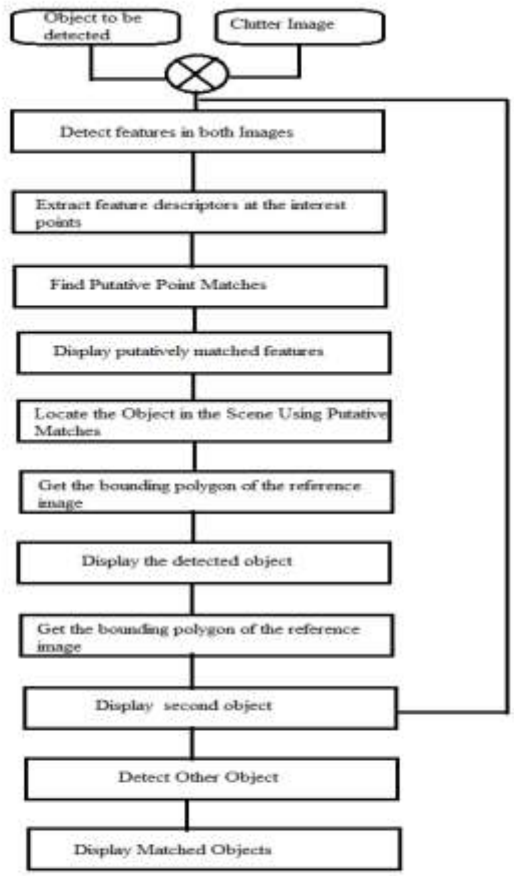

Fig.2:Flowchart of system

IV.CONCLUSION

To address the problem of rotation-invariant non rigid point set matching, we proposed two methods for shape representation. The SC feature descriptor was used, and we constructed graphs on point sets, where edges are used to determine the orientations of SCs. This enables the proposed methods rotation invariant. The structures of our shape representations facilitate the use of DP for optimization. The strong discriminative nature of SC, the calculated robust orientations of SCs, and the global optimality of DP make our methods robust to various types of disturbances, particularly clutters.

The proposed methods were tested on both synthetic and real data in comparison with several representative methods. The results show that our methods, particularly MSTT, clearly outperform other methods in terms of robustness against clutter. The proposed methods are very useful for tasks involving detection and matching of shapes in cluttered scenes, where the initial poses of the shapes may not be known.

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REFERENCES

[1] N. Aronszajn. Theory of Reproducing Kernels. *Trans. of the American Mathematical Society*, 68(3):337–404, 1950.

[2] A. Basu, I. R. Harris, N. L. Hjort,and M. C. Jones. Robust and Efficient Estimation by Minimising A Density Power Divergence.*Biometrika*, 85(3):549–559, 1998.
[3] S. Belongie, J. Malik, and J. Puzicha. Shape Matching and Object Recognition Using Shape Contexts. *TPAMI*, 24(24):509–522, 2002.
[4] P. J. Besl and N. D. McKay. A Method for Registration of 3-D Shapes. *TPAMI*, 14(2):239–256, 1992.
[5] L. G. Brown. A Survey of Image Registration Techniques. *ACM Computing Surveys*, 24(4):325–376, 1992.
[6] H. Chui and A. Rangarajan. A new point matching algorithm for Non-rigid registration. *CVIU*, 89:114–141, 2003.
[7] A. W. Fitzgibbon. Robust Registration of 2D and 3D Point Sets. *Image and Vision Computing*, 21:1145–1153, 2003.
[8] P. J. Huber. *Robust Statistics*. John Wiley & Sons, New York, 1981.
[9] B. Jian and B. C. Vemuri. Robust Point Set Registration Using Gaussian Mixture Models. *TPAMI*, 33(8):1633–1645, 2011.
[10] A. E. Johnson and M. Hebert. Using Spin-Images for Efficient Object Recognition in Cluttered 3-D Scenes. *TPAMI*, 21(5):433–449, 1999.
[11] J.-H. Lee and C.-H. Won. Topology Preserving Relaxation Labeling for Non rigid Point Matching. *TPAMI*, 33(2):427–432, 2011.
[12] X. Li and Z. Hu. Rejecting Mismatches by Correspondence Function.*IJCV*, 89(1):1–17, 2010.
[13] D. Lowe. Distinctive Image Features from Scale-Invariant Keypoints.*IJCV*, 60(2):91–110, 2004.
[14] B. Luo and E. R. Hancock. Structural Graph Matching Using the EM Algorithm and Singular Value Decomposition. *TPAMI*,23(10):1120–1136, 2001.
[15] J. Ma, J. Zhao, Y. Zhou, and J. Tian. Mismatch Removal via Coherent Spatial Mapping. In *ICIP*, 2012.
[16] C. A. Micchelli and M. Pontil. On Learning Vector-Valued Functions .*Neural Computation*, 17(1):177–204, 2005.
[17] A. Myronenko and X. Song. Point Set Registration: Coherent PointDrift. *TPAMI*, 32(12):2262–2275, 2010.
[18] R. Rifkin, G. Yeo, and T. Poggio. Regularized Least-Squares Classification.In *Advances in Learning Theory: Methods, Model andApplications*, 2003.
[19] S. Rusinkiewicz and M. Levoy. Efficient Variants of the ICP Algorithm.In *3DIM*, pages 145–152, 2001.
[20] D.W. Scott. Parametric Statistical Modeling by Minimum Integrated Square Error. *Technometrics*, 43(3):274–285, 2001.
[21] L. Torresani, V. Kolmogorov, and C. Rother. Feature Correspondence via Graph Matching: Models and Global Optimization. In *ECCV* ,pages 596–609, 2008.
[22] Y. Tsin and T. Kanade. A Correlation-Based Approach to RobustPoint Set Registration. In *ECCV*, pages 558–569, 2004.
[23] G. Wahba. *Spline Models for Observational Data*. SIAM, Philadelphia,PA, 1990.
[24] A. L. Yuille and N. M. Grzywacz. A Mathematical Analysis of theMotion Coherence Theory. *IJCV*, 3(2):155–175, 1989.
[25] A. Zaharescu, E. Boyer, K. Varanasi, and R. Horaud. Surface FeatureDetection and Description with Applications to Mesh Matching. In*CVPR*, pages 373–380, 2009.
[26] J. Zhao, J. Ma, J. Tian, J. Ma, and D. Zhang. A Robust Method forVector Field Learning with Application to Mismatch Removing. In*CVPR*, pages 2977–2984, 2011.