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A novel approach for identification and localization of rotated objects

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ABSTRACT

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. Point matching is an important aim in the research work. A digital image may undergo any arbitrary translational, rotational changes because of which the object shape may change. In this paper we present a novel approach for shape and feature matching using putative point matching.

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 no rigid point set Matching is particularly difficult because the possible no 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.

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.

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.

To achieve the above goal, we have to build this architecture. Regarding the architecture, we have many choices to implement according to the already presented approaches in this field. Some of these approaches depend on the extraction of data from the image in the form of vectors, vectors indicating positions and vectors emoting intensity gradients for those positions, in order to compare in a later stage with the images found in the database. Another approach is related to neural networks where the architecture is designed of many layers that consist of neurons to compare to the saved images, and this approach will be used in our implementation.

Previous Work

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. Insofar as a method attempts to solve either the correspondence or the transformation alone, it can be regarded as an independent estimation approach. On the contrary, if a method tries to find the solution for both variables, usually via an alternating update scheme, it can be regarded as a joint estimation approach. We use this distinction to orient our description of previous research.

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 principal axis 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.

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A more sophisticated technique is the Hough Transform [2, 3]. The transformation parameter space is divided into small bins, where each bin represents a certain configuration of transformation parameters. The points are allowed to vote for all the bins and the bin which gets 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].

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 eigen vectors 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.

The examples shown in [22] demonstrate that the method is capable of aligning point-sets which undergo non-rigid deformations. It is clear that the shape eigen-modes do provide enough information to differentiate the points at a global level. However, when examined at a more local and detailed level, their results [23] also indicate the correspondences found are not very accurate. Besides accuracy, another major limitation of these algorithms is that they cannot tolerate outliers. Outliers can cause serious changes to the deformation modes which invalidates the resulting correspondences.

Another approach recently proposed in [5, 6, and 24] adopts a more probabilistic strategy. A new shape descriptor, called the "shape context", is defined for correspondence recovery and shape-based object recognition. For each point chosen, lines are drawn to connect it to all other points. The length as well as the orientation of each line is calculated. The distribution of the length and the orientation for all lines (they are all connected to the first point) is estimated through histogram. This distribution is used as the shape context for the first point. Basically, the shape context captures the distribution of the relative positions between the currently chosen point and all other points. The shape context is then used as the shape attributes for the chosen point. The correspondence can then be decided by comparing each point's attributes in one set with the attributes in the other. Since attributes and not relations are compared, the search for correspondence can be conducted much more easily. Or in more technical terms, the correspondence is obtained by solving a relatively easier bipartite matching problem rather than a more intractable graph matching problem [26]. After the correspondences are obtained, the point set is warped and the method repeated. Designed with the task of object recognition in mind, this method has demonstrated promising performance in matching shape patterns such as hand-written characters. The algorithm's ability to handle complex patterns and large deformations is under investigation.

Methodology

To overcome this accidental alignment problem, we propose a feature detection & matching approach called Putative Feature Point Matching (PFPM) algorithm consisting of the following the key ingredients:

1. We detect salient contours using bottom-up segmentation or contour grouping. Long contours are more distinctive, and maintaining contours as integral tokens for matching removes many false positives due to accidental alignment.
2. We break the model feature into its informative semantic parts, and explicitly check which subset of model feature parts is matched. Missing critical model parts can signal an accidental alignment between the image and model.
3. We seek holistic feature matching. We measure feature features from a large spatial extent, as well as long-range contextual relationships among object parts. Accidental alignments of holistic feature descriptors between image and model are unlikely. Our putative feature point matching algorithm reduces to finding a maximal, holistic matching between a set of image contours and a set of model parts. It searches over figure/ground labeling of the image and model contours, and correspondences between them. It is important to note that, in general, image contours and model contours do not correspond one-to-one. The holistic matching occurs only by considering a set of 'figure' contours together. To formulate this set-to-set matching task, we define control points sampled on and around the image and model contours.

PFPM Algorithm

- Read the reference image & target image.
- Detect feature points in both Images, Visualize the strongest feature points found in the target image.(Go to Step 1 of abcd)
- Extract feature descriptors at the interest points in both images. (Go to Step 1 of xyz)
- Find putative point matches; match the features using their descriptors. (Go to Step 1 of Ftrmtch & fundamentalff)
- Display putatively matched features.
- Locate the object in the scene using putative matches. Display the matching point pairs.
- Get the bounding polygon of the reference image.
- Display the detected object.
- Get the bounding polygon of the reference image.
- Detect a second object by using the same steps as before.
- Repeat Steps 1-6
- Display Both Object

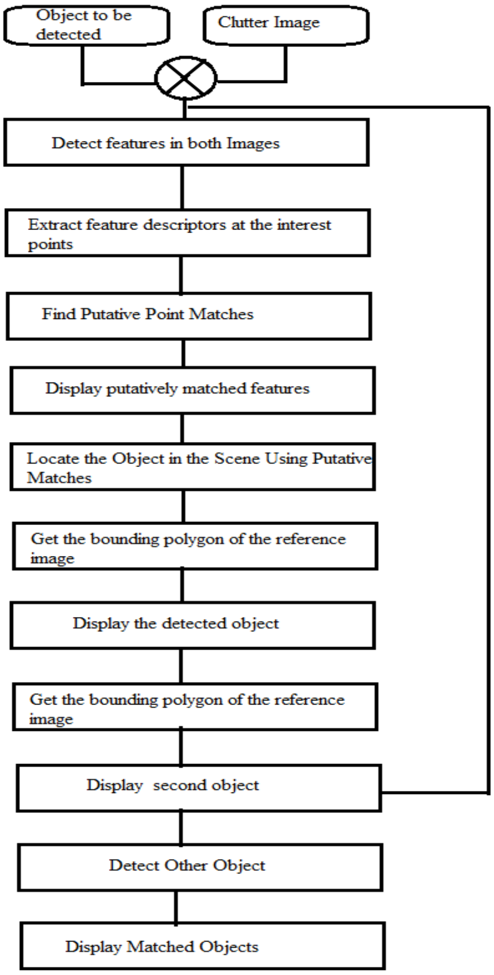
Experimental Results

The output of each step after its execution is shown using screen shots of each stage.

In our project, the main motive is to detect the object which has some degree of rotation. Means not exactly same in clutter image. In this example we rotate the image of book. Our task is to detect the book in clutter image.

Detect feature points in both images; visualize the strongest feature points found in the target image. Here we find putative point matches, match the features using their descriptors in both of Images i.e. from object to be detected & cluttered Image. After finding putatively matched points we display putatively matched features. We mark the strongly selected feature point using polygons. Here we define the number of strongest feature to be selected.

Flowchart of proposed system



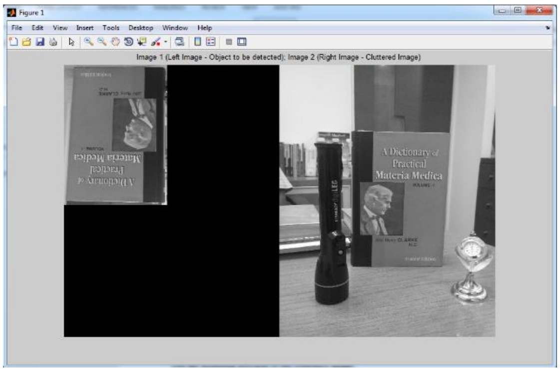


Fig 1. Read the reference image & target image.

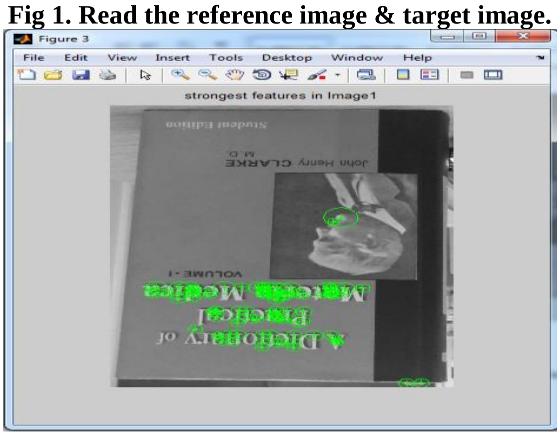


Fig 2 Strongest feature to be selected in object Image

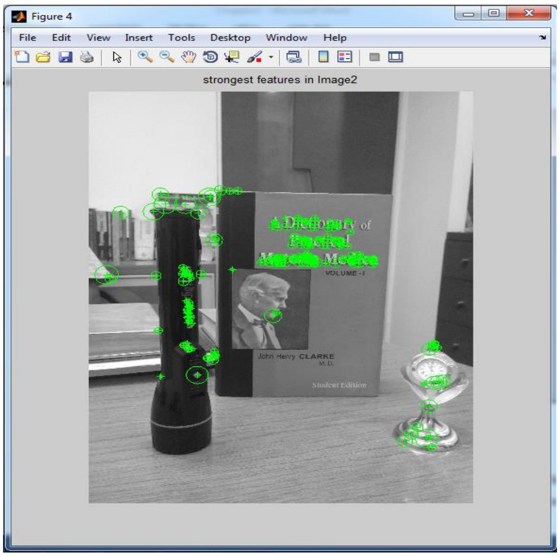


Fig 3. Strongest feature to be selected in reference image.

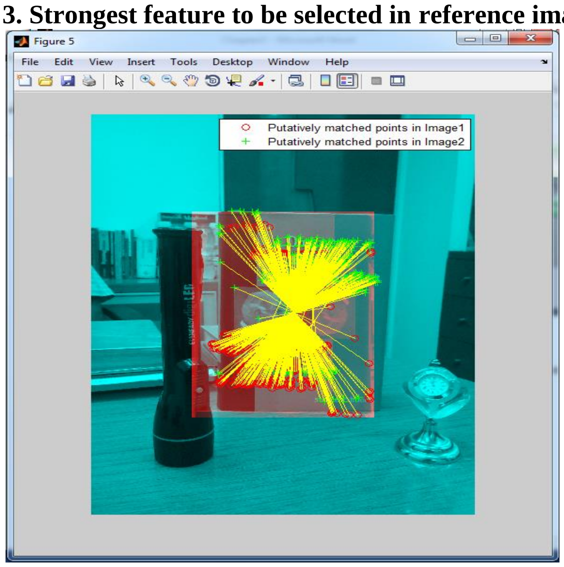


Fig 4. Locate the Object in the Scene Using Putative Matches Display the matching point pairs.

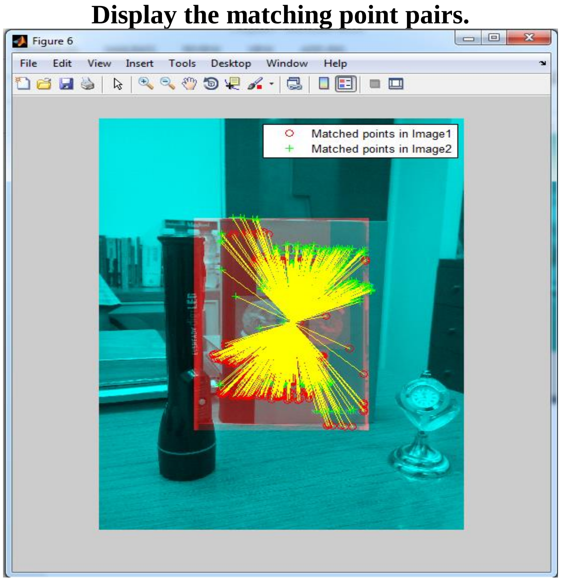


Fig 5. Matched Objects.

Conclusion

The feature-based methods for image registration frequently encounter the correspondence problem, regardless of whether points, lines, curves or surface parameterizations are used. Feature-based image matching requires, to automatically solving 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. Hence a novel method has been formulated for feature-based non-rigid registration in cluttered images.

An algorithm called as Putative Feature Point Matching (PFPM) algorithm has been designated which concentrate not only on similar features of images but also on its shape, non-rigid points, and its degree of rotation. The objective of this paper was to eliminate the drawbacks of earlier algorithms giving correct correspondence between the source and target images. Further the experimental results prove the robust of algorithm involving degree of rotation detecting our object of interest.

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