A Keygraph Classification Framework for Real-Time Object Detection

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Abstract

In this paper, we propose a new approach for keypoint-based object detection. Traditional keypoint-based methods consist in classifying individual points and using pose estimation to discard misclassifications. Since a single point carries no relational features, such methods inherently restrict the usage of structural information to the pose estimation phase. Therefore, the classifier considers purely appearance-based feature vectors, thus requiring computationally expensive feature extraction or complex probabilistic modelling to achieve satisfactory robustness. In contrast, our approach consists in classifying graphs of keypoints, which incorporates structural information during the classification phase and allows the extraction of simpler feature vectors that are naturally robust. In the present work, 3-vertices graphs have been considered, though the methodology is general and larger order graphs may be adopted. Successful experimental results obtained for real-time object detection in video sequences are reported.

1 Introduction

Object detection is one of the most classic problems in computer vision and can be informally defined as follows: given an image representing an object and another, possibly a video frame, representing a scene, decide if the object belongs to the scene and determine its pose if it does. Such pose consists not only of the object location, but also of its scale and rotation. The object might not even be necessarily rigid, in which case more complex deformations are possible. We will refer to the object image as our model and, for the sake of simplicity, refer to the scene image simply as our frame.

Recent successful approaches to this problem are based on keypoints [5, 1, 4, 6]. In such approaches, instead of the model itself, the algorithm tries to locate a subset of points from the object. The chosen points are those that satisfy desirable properties, such as ease of detection and robustness to variations of scale, rotation and brightness. This approach reduces the problem to supervised classification where each model keypoint represents a class and feature vectors of the frame keypoints represent input data to the classifier.

A well-known example is the SIFT method proposed by Lowe [5]. The most important aspect of this method relies on the very rich feature vectors calculated for each keypoint: they are robust and distinctive enough to allow remarkably good results in practice even with few vectors per class and a simple nearest-neighbor approach. More recent feature extraction strategies, such as the SURF method proposed by Bay, Tuytelaars and van Gool [1], are reported to perform even better.

The main drawback of using rich feature vectors is that they are usually complex or computationally expensive to calculate, which can be a shortcoming for real-time detection in videos, for example. Lepeit and Fua [4] worked around this limitation by shifting much of the computational burden to the training phase. Their method uses simple and cheap feature vectors, but extracts them from several different images artificially generated by applying changes of scale, rotation and brightness to the model. Therefore, robustness is achieved not by the richness of each vector, but by the richness of the training set as a whole.
Training

1. Detect keypoints in the model.
2. Extract feature vectors from each keypoint.
3. Use the feature vectors to train a classifier whose classes are the keypoints. 
   The accuracy must be reasonably high, but not necessarily near-perfect.

Classification

1. Detect keypoints in the frame.
2. Extract feature vectors from each keypoint.
3. Apply the classifier to the feature vectors in order to decide if each frame 
   keypoint is sufficiently similar to a model keypoint. As near-perfect accu-
   racy is not required, several misclassifications might be done in this step.
4. Use an estimation algorithm to determine a pose spatially coherent with 
   a large enough number of classifications made during the previous step. 
   Classifications disagreeing with such pose are discarded as outliers.

Figure 1: Traditional framework for keypoint-based object detection.

Regardless the choice among most of such methods, keypoint-based approaches traditionally follow 
the same general framework, described in Figure 1.

A shortcoming of this framework is that structural information, such as geometric and topological 
relations between the points, only play a role in the pose estimation step: they are completely absent 
of all classification steps. Therefore, the entire burden of describing a keypoint lies on individual 
appearance information, such as the color of pixels close to it. Recently, Özuysal, Fua and Lepetit [6] 
proposed a less individual approach by defining a probabilistic modelling scheme where small groups 
of keypoints are considered. However, since a purely appearance-based feature vector set is used under 
this model, there is still an underuse of structure in their approach.

In this paper, we propose an alternative framework that, instead of classifying single keypoints, 
classifies sets of keypoints using both appearance and structural information. Since graphs are math-
ematical objects that naturally model relations, they are adopted to represent such sets. Therefore, 
the proposed approach is based on supervised classification of graphs of keypoints, henceforth referred 
as keygraphs. A general description of our framework is given by Figure 2.

The idea of using graphs built from keypoints to detect objects is not new: Tang and Tao [9] had 
success with dynamic graphs defined over SIFT points. Their work, however, shifts away from the 
classification approach and tries to solve the problem with graph matching. Our approach, in contrast, 
still reduces the problem to supervised classification, which is more efficient. In fact, it can be seen as 
a generalization of the traditional methods, since a keypoint is a single-vertex graph.

This paper is organized as follows. Section 2 introduces the proposed framework, focusing on the 
advantages of using graphs instead of points. Section 3 describes a concrete implementation of the 
framework, where 3-vertices keygraphs are used, and some successful experimental results that this 
implementation had for real-time object detection. Finally, in Section 4 we present our conclusions.

2 Keygraph Classification Framework

A graph is a pair (\(\mathcal{V},\mathcal{E}\)), where \(\mathcal{V}\) is an arbitrary set, \(\mathcal{E} \subseteq \binom{\mathcal{V}}{2}\) and \(\binom{\mathcal{V}}{2}\) denotes the family of all subsets 
of \(\mathcal{V}\) with cardinality 2. We say that \(\mathcal{V}\) is the set of vertices and \(\mathcal{E}\) is the set of edges. We also say that 
the graph is complete if \(\mathcal{V} = \binom{\mathcal{V}}{2}\) and that \((\mathcal{V}',\mathcal{E}')\) is a subgraph of \((\mathcal{V},\mathcal{E})\) if \(\mathcal{V}' \subseteq \mathcal{V}\) and \(\mathcal{E}' \subseteq \mathcal{E} \cap \binom{\mathcal{V}}{2}\).

Given a set \(\mathcal{S}\), we denote by \(\mathcal{G}(\mathcal{S})\) the complete graph whose set of vertices is \(\mathcal{S}\).

Those definitions allow us to easily summarize the difference between the traditional and the
### Training

1. Detect keypoints in the model.
2. Build a set of keygraphs whose vertices are the detected keypoints.
3. Extract feature vectors from each keygraph.
4. Use the feature vectors to train a classifier whose classes are the keygraphs. The accuracy must be reasonably high, but not necessarily near-perfect.

### Classification

1. Detect keypoints in the frame.
2. Build a set of keygraphs whose vertices are the detected keypoints.
3. Extract feature vectors from each keygraph.
4. Apply the classifier to the feature vectors in order to decide if each frame keygraph is sufficiently similar to a model keygraph. As near-perfect accuracy is not required, several misclassifications might be done in this step.
5. Use an estimation algorithm to determine a pose spatially coherent with a large enough number of classifications made during the previous step. Classifications disagreeing with such pose are discarded as outliers.

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**Figure 2:** Proposed framework with the main differences emphasized.

**Figure 3:** Even a very simple graph with three vertices has a large number of subgraphs.

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**proposed frameworks. Both have the same outline: define certain universe sets from the model and the frame, detect key elements from those sets, extract feature vectors from those elements, train a classifier with the model vectors, apply the classifier to the frame vectors and analyze the result with a pose estimation algorithm. The main difference lies on the first step: defining the universe set of an image. In the traditional framework, since the set of keypoints $K$ represents the key elements, this universe is the set of all image points. In the proposed framework, while the detection of $K$ remains, the universe is the set of all subgraphs of $G(K)$. In the following subsections, we describe the fundamental advantages of such difference in three steps: the key element detection, the feature vector extraction and the pose estimation.**

#### 2.1 Keygraph Detection

As it can be seen on Figure 3, one of the most evident differences between detecting a keypoint and detecting a keygraph is the size of the universe set: the number of subgraphs of $G(K)$ is exponential on the size of $K$.

This implies that a keygraph detector must be much more restrictive than a keypoint detector if we are interested in real-time performance. Such necessary restrictiveness, however, is not hard to obtain because graphs have structural properties to be explored that individual keypoints do not. Those properties can be classified in three types: *combinatorial, topological* and *geometric*. Figure 4 shows how those three types of structural properties can be used to gradually restrict the number of
considered graphs.

2.2 Partitioning the Feature Vectors

A natural approach for extracting feature vectors from keygraphs is by translating all the keygraph properties, regardless if they are structural or appearance-based, into scalar values. However, a more refined approach that allows to take more advantage of the power of structural information has been adopted.

This approach consists in keeping the feature vectors themselves appearance-based, but partitioning the set of vectors according to structural properties. There are two motivations for such approach: the first one is the fact that a structural property, alone, may present a strong distinctive power. The second one is the fact that certain structural properties may assume boolean values for which a translation to a scalar does not make much sense. Figure 5 gives a simple example that illustrates the two motivations.

By training several classifiers, one for each subset given by the partition, instead of just one, we not only satisfy the two motivations above, but we also improve the classification from both an accuracy and an efficiency point of view.

2.3 Naturally Robust Features

For extracting a feature vector from a keygraph, there exists a natural approach by merging multiple keypoint feature vectors extracted from its vertices. However, a more refined approach may be derived. In traditional methods, a keypoint feature vector is extracted from color values of the points that
belong to a certain patch around it. This approach is inherently flawed because, as Figure 6 shows, such patches are not naturally robust to scale and rotation.

Traditional methods work around this flaw by improving the extraction itself. Lowe [5] uses a gradient histogram approach, while Lepetit and Fua [4] rely on the training with multiple synthetic views.

With keygraphs, in contrast, the flaw does not exist in the first place, because they are built on sets of keypoints. Therefore, they allow the extraction of relative features that are naturally robust to scale and rotation without the need of sophisticated extraction strategies. Figure 7 shows a very simple example.

2.4 Pose Estimation by Voting

A particular advantage of the SIFT feature extraction scheme relies on its capability of assigning, to each feature vector, a scale and rotation relative to the scale and rotation of the model itself. This greatly reduces the complexity of pose estimation because each keypoint classification naturally induces a pose that the object must have in the scene if such classification is correct. Therefore, one can obtain a robust pose estimation and discard classifier errors by simply following a Hough [3] transform procedure: a quantization of all possible poses is made and each evaluation from the classifier registers a vote for the corresponding quantized pose. The most voted pose wins.

The same procedure can be used with keygraphs, because relative properties of a set of keypoints can be used to infer scale and rotation. It should be emphasized, however, that the viability of such strategy depends on how rich the structure of the considered keygraphs is. Figure 8 has a simple example of how a poorly chosen structure can cause ambiguity during the pose estimation.
3 Implementation and Results

In this section we will present the details of an implementation of the proposed framework that was made in C++ with the OpenCV [8] library. To illustrate our current results with this implementation, we describe an experiment on which we attempted to detect a book in real-time with a webcam, while varying its position, scale and rotation. We ran the tests in an Intel® Core™2 Duo T7250 with 2.00GHz and 2 GB of RAM. A 2-megapixel laptop webcam was used for the detection itself and to take the single book picture used during the training.

3.1 Good Features to Track

For keypoint detection we used the well-known good features to track detector proposed by Shi and Tomasi [7], that applies a threshold over a certain quality measure. By adjusting this threshold, we are able to control how rigid is the detection. A good balance between accuracy and efficiency was found in a threshold that gave us 79 keypoints in the model, as it can be seen on Figure 9.

Figure 8: Example of pose estimation ambiguity. The white rectangle indicates the pose of a certain 2-vertex graph in a frame. If a classifier evaluates this graph as being the model keygraph indicated in Figure 7, there would be two possible coherent rotations.

Figure 9: Result of the good features to track algorithm.
Figure 10: Scalene triangle with $\theta_1 < \theta_2 < \theta_3$. In this case, if we pass through the three vertices in increasing order of internal angle, we have a counter-clockwise movement.

Figure 11: Corner chrominance extraction. The gray segments define a limit for the size of the projected lines. The white points defining the extremities of those lines are positioned according to a fraction of the edge they belong to. In the above example the fraction is $1/3$.

3.2 Thick Scalene Triangles

For keygraph detection we selected 3-vertices complete graphs whose induced triangle is sufficiently thick and scalene. More formally, that means each one of the internal angles in the triangle should be larger than a certain threshold and the difference between any two internal angles is larger than another threshold. The rationale behind this choice is increasing structure richness: the vertices of a excessively thin triangle are too close of being collinear and high similarity between internal angles could lead to the pose estimation ambiguity problem mentioned in the previous section.

In our experiment, we established that no internal angle should have less than 5 degrees and no pair of angles should have less than 5 degrees of difference. To avoid numerical problems, we also added that no pair of vertices should have less than 10 pixels of distance. Those three thresholds limited drastically the number of keygraphs: out of $79 \cdot 78 \cdot 77 = 474,474$ possible 3-vertices subgraphs, the detector considered 51,002 keygraphs.

The partitioning of the feature vector set is made according to three structural properties. Two of them are the values of the two largest angles. Notice that, since the internal angles of a triangle always sum up to 180 degrees, considering all angles would be redundant. The third property refers to a clockwise or counter-clockwise direction defined by the three vertices in increasing order of internal angle. Figure 10 has a simple example.

In our experiment we established a partition in $2 \cdot 36 \cdot 36 = 2592$ subsets: the angles are quantized by dividing the interval $(0, 180)$ in 36 bins. The largest subset in the partition has 504 keygraphs, a drastic reduction from the 51,002 possible ones.

3.3 Corner Chrominance Extraction

Figure 11 illustrates the scheme for extracting a feature vector from a keygraph. Basically, the extraction consists in taking several internal segments and, for each one of them, to calculate the mean chrominance of all pixels intersected by the segment.
The chrominance values are obtained by converting the model to the HSV color space and considering only the hue and saturation components. The segments are obtained by evenly partitioning bundles of lines projected from the vertices. Finally, the size of those projected lines is limited by a segment whose extremities are points in the keygraph edges.

This scheme is naturally invariant to rotation. Invariance to brightness is ensured by the fact that we are considering only the chrominance and ignoring the luminance. Finally, the invariance to scale is ensured by the fact that the extremities mentioned above are positioned in the edges according to a fraction of the size of the edge that they belong to, and not by any absolute value.

3.4 Results with Delaunay Triangulation

We could not use, during the classification phase, the same keygraph detector we used during the training phase: it does not reduce enough the keygraph set size for real-time performance. We use an alternative detector that gives us a smaller subset of the set the training detector would give.

This alternative detector consists in selecting thick scalene triangles from a Delaunay triangulation of the keypoints. A triangulation is a good source of triangles because it covers the entire convex hull of the keypoints. And the Delaunay triangulation, in particular, can be calculated very efficiently, for example with the $\Theta(n \log n)$ Fortune [2] algorithm.

Figure 12 shows some resulting screenshots. A full video can be seen at

http://www.vision.ime.usp.br/~mh/gbr2009/book.avi.

4 Conclusion

We presented a new framework for keypoint-based object detection that consists on classifying keygraphs. With an implementation of this framework, where the keygraphs are thick scalene triangles, we have shown successful results for real-time detection after training with a single image.

The framework is very flexible and is not bounded to a specific keypoint detector or keygraph detector. Therefore, room for improvement lies on both the framework itself and the implementation of each one of its steps. We are currently interested in using more sophisticated keygraphs and in adding the usage of temporal information to adapt the framework to object tracking.

Finally, we expect to cope with 3D poses (i.e. out-of-plane rotations) by incorporating additional poses to the training set. These advances will be reported in due time.
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