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Coherent Theme Discovery in Images Based On Visual Pattern

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ABSTRACT: Discovering Thematic objects that appear frequently in a number of images is a challenging problem, due to the appearance variations of the same common object and the enormous computational cost involved in exploring the huge solution space, including the location, scale, and the number of common objects. We characterize each image as a collection of visual primitives and propose a novel bottom up approach to gradually prune local primitives to recover the whole common object. A multi-layer candidate pruning procedure is designed to accelerate the image data mining process. Our solution provides accurate localization of the common object, thus is able to crop the common objects despite their variations due to scale, view-point, lighting condition changes. Moreover, it can extract common objects even with few numbers of images. Experiments on challenging image datasets validate the effectiveness and efficiency of our method.

KEYPOINTS: visual primitives, Theme object Discovery, data mining, multilayer candidate pruning

I. INTRODUCTION

Given a collection of images to distinguish commonly appearing objects. Each sequence contains many occurrences of the same theme object but not every frame contains an Occurrence of the same theme object but not every frame contains an occurrence. The discovered theme object is localized by the red bounding box. Figure 1 illustrates the examples of theme object discovery, in that we need to recognize or discover the frequently appearing objects that are illustrative of the visual contents. This frequently appearing of objects is called as theme or thematic objects.

Figure.1. Examples of Theme object discovery

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There are to automatically discover thematic objects, there are two major challenges first of all, there lacks a priori knowledge of the thematic visual pattern, thus not known in advance 1] the shapes and appearance of the thematic objects. 2] The locations and scales of thematic objects. 3] The total no. of thematic objects. Moreover, the same thematic object can look quite different when presented from different viewpoints, scales, or under different lighting conditions not to mention partial occlusions. From the previous success in mining text data, one popular solution to image data mining is to transfer on image in to a "visual document" by clustering the local visual features in to "visual words". Then traditional text mining methods can be directly applied to image data.

Visual patterns are formation of visual primitives that appear commonly in image datasets. As shown in fig.1.2 the multiple visual patterns in image data can represents the frequently appearing image feature, e.g. a face pattern collected of two eyes, a nose and a mouth; bedroom including a bed, a lamp, a vase and so on; or a human being action that narrate postures and movements of body, e.g. a bent leg layover spin motion before mining visual primitives from image data.

Figure .2 Multiple visual pattern

Bottom up approach begins from the local layout of visual primitives to detect common visual pattern in image data. There is multiple profit of bottom up approach can be widely registered for their data driven feature. Second, bottom – up techniques can clearly include varieties of contexts such as spatial co- occurrence of multiple visual primitives and correlation between pairs of visual primitives. Third, bottom-up methods are simple to execute.

II.LITERATURE SURVEY

Introduced the procedure to define a thematic object as the key object that frequently appears and is the representative of the visual contents. Successful discovery of the thematic object is helpful for object search and tagging, and understanding, etc. However, this task is challenging because there lacks *a* priori knowledge of the thematic objects, such as their shapes, scales, locations, and times of re-occurrences, and the thematic object of interest can be under severe variations in appearances due to viewpoint and lighting condition changes, scale variations, etc. Instead of using a top–down generative model to discover thematic visual patterns, we propose a novel bottom–up approach to gradually prune uncommon local visual primitives and recover the thematic objects. A multilayer candidate pruning procedure is designed to accelerate the image data mining process. Our solution can efficiently locate thematic objects of various sizes and can tolerate large appearance variations of the same thematic object. Experiments on challenging image data sets with existing method [1].

Hongliang Li and King Nga Ngan introduced a procedure to indentify the existence of co-saliency from an image pair that may have identical objects in common. Here the co-saliency is described as the multi-image saliency map and linear combinations of the single –image saliency map. SISM is described to design local attention. And in MISM, the image pairs are divided into a spatial pyramid to construct a co-multilayer graph. Each node represented in the graph

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consists of two types of visual descriptors like color and texture properties. A normalized single pair Sim-Rank algorithm is used to calculate the similarity score [2].

T.K.Puneeth kumar, R. Jey**a,** the object that appears frequently in a set or sequence of images is defined as thematic object. In a collection of image sequences, thematic object as a key object. Detecting common objects that appear frequently in a set of images is an intriguing problem. It also lacks the prior knowledge in common pattern. System is proposed so that it overcomes the above problems. System consists of Pre-processing, which enhances the data images prior to computational processing. SURF algorithm is used for detecting, extracting and for matching the feature points with respect to geometric transformations. Obtained feature points from the different images are compared to determine the common feature from the data images. This solution helps to locate the thematic objects much more easily within less time.[3]

J. Matas, Chum, M.Urban, T. Pajdla , here a new set of image elements that are put into correspondence, the so called extremal regions, is introduced. Extremal regions possess highly desirable properties: the set is closed under continuous transformation of image coordinates and Monotonic transformation of image intensities. An efficient (near linear complexity) and practically fast detection algorithm (near frame rate) is presented for an affinity-invariant stable subset of extremal regions, the MSER[4].

Bryan C., Russell1 Alexei A. Efros, Josef Sivic, Given a large dataset of images, we seek to automatically determine the visually similar object and scene classes together with their image segmentation. To achieve this we combine two ideas: (i) that a set of segmented objects can be partitioned into visual object classes using topic discovery models from statistical text analysis; and (ii) that visual object classes can be used to assess the accuracy of segmentation. To tie these ideas together we compute multiple segmentations of each image and then: (i) learn the
Object classes; and (ii) choose the correct segmentations.[5].

III. SYSTEM MODEL

The below figure 2, explains the block diagram to identify the theme objects in videos and images. Initially the images in the database are divided into sectors which may represent an object defined by R. Features in the form of visual primitives are extracted for the formation of the feature vector. Further is the Feature matching, where the features extracted from the input image are matched with the stored template or reference model and a recognition decision is made? The similarity among the similarly themed objects should be maximized; hence the uncommon features are to be pruned (removed). For the purpose of pruning, *k-SSN* is which estimates the similarity co-efficient among the similarly themed objects. To discover theme object in a video, we characterize video as a collection of video frames, each frame as an image sequence. Each image is characterized by collection of local visual primitives.
A visual primitive is a property of an image located on a single point or small region.
The local features of an object are color or gray value of a pixel. For object recognition, the local feature must be invariant to illumination changes, point of view scale changes and changes in angles. We match the visual primitives to identify the presence theme object in a video. The match function is applied to the patch descriptor to find there is any match between the given image and the frames of the video. Sector localization of the regions is supposed to be containing the theme object. The branch and bound algorithm can be used for the extraction of the required sector.

IV.IMPLEMENTATION DETAIL

Overview

To discover theme object from given a collection of T images $\mathcal{D} = \{\boldsymbol{I}i\}$, it describes every image $\boldsymbol{I}i= \{p1. . . . pm\}$ by a number of visual primitives. To gradually reject uncommon visual primitives $p\in I$ to recover R^*. In the previous step, we discard uncommon primitive's p that finds few matches among the rest of images in $\mathcal{D}$. The remained set of visual primitives is described as $D_1 \subseteq D$. For the further verification $P \in D^l$, its spatial neighbors form a visual group $G_p=\{p,p_1^{NN} ,\ldots, p_k^{NN} \}$, where P_i^{NN} is one of the nearest neighbors of p in the image. A commonness score $C(p)$ will be assigned to each visual primitive p. Visual primitive p has a positive commonness score if its visual group Gp

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frequently appears among the data set $\mathcal{D}$, and vice versa, whereas it has a negative commonness score if it repeats rarely. The thematic object can be located as the sub image region R ⊂I that contains the most common primitives.

V. MULTILAYER CANDIDATE PRUNING

Here we can examine the commonness of each primitive by treating its k-SNN5. The best performances for primitives *p* depends on size of *k* as it increases. The number of SNN is k for groups in D_1, the similarity between two sets *Gq* and *Gp*, *Sim {Gp , Gq}* can be defined as a matching problem.

$$Sim(G_p,G_q) \triangleq \max_{f\epsilon F}\sum_{i=1}^{|Gp|} s(P_i,f(P_i)) \quad (1)$$

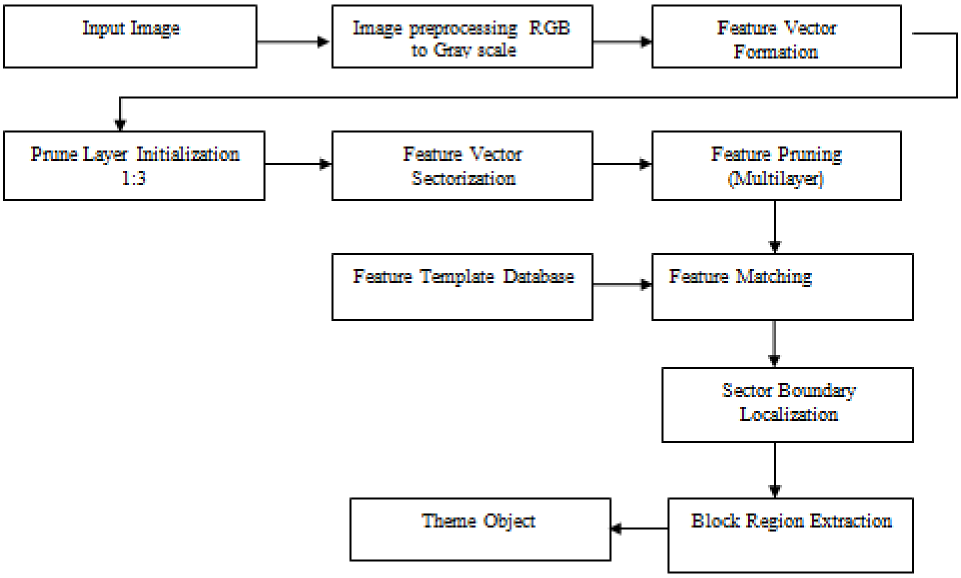

Figure 3 System block diagram

Here *f* denotes a matching between two point sets *Gp* and *Gq*, *F* is the complete set of all possible matching. Given a group *Gp*, its supportive set consists of the groups in the rest of images that match *Gp*.

$$S_p = \{G_q: Sim(G_p,G_q) > \theta\} \quad (2)$$

After rejecting uncommon groups, an even smaller candidate set is obtained as D^2. For the total *L* layers denoted as D^L the final set, we obtain a filtration, $D^L \subseteq \ldots \subseteq D^1 \subseteq D$ and spatial neighborhood size $K^L >> \ldots > K^1 > 0$ As compare to D^1 , a visual primitive $P \in D^l$ $(2 \leq l \leq L)$ responds to a larger spatial neighborhood which belongs to be a part of a common theme object. Multilayer checking assigns a commonness score for each *p*. For particular primitive $P \in \{ D^L \ldots D^l \}$, its commonness score is assigned with a positive value. Whereas for the primitives in that is, $D / D^l = \{P: P \in D \cdot P \in D^l \}$. Its commonness score is designated as s negative value. The commonness score designated to each *p* as given below. Here Ʈ is assigned as the negative vote value.

$$C(P) = \begin{cases} K^l \text{ if } P \in \{ D^l \backslash D^{l+1} \}, 1 \leq l \leq L \\ Ʈ \text{ if } P \in \{ D \backslash D^l \} \end{cases} \quad (3)$$

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VI. DETECTING THEME OBJECT

As the commonness score C (p) is obtained, then it can detect the theme object in each image using a bounding box. $\boldsymbol{Ii}$, we search for the bounding box R* with the maximum commonness score.

$$\boldsymbol{R}^{*} = \underset{\boldsymbol{R}\subseteq \boldsymbol{I}}{\mathbf{argmax}} \sum_{P\in R} C(P) = \underset{\boldsymbol{R}\in\wedge}{\mathbf{argmax}}\ F(R) \tag{4}$$

Where F(R) $\sum_{P\in R} C(P)$ is the objective function and ^ denotes the candidate set of all valid sub images in $\boldsymbol{Ii}$. To speed up this localization process, we apply the branch and bound search. The target bounding box R* is determined by four parameters, i.e., top, bottom, left, and right positions in the image.
The below figures shows the sample results as figure 4 is the input selected image set. Figure 5 shows the identification of theme object in images that is tracking object in the all images.
The cropping of object from the images are identified as, first features of each object in the image are extracted, pattern matching is done the having desired features in the hand. The x and y directional flow components are calculated from the gradient of the image. The secondary differences in the x and y components of the image are used to find the final flow of intensities respectively. The laplacian gives the visualization of the edges for the proper tracking of the object in the images. This data are used for the extraction of visual primitives which will be further used by the classification algorithm.

VII. RESULT AND DISCUSSION

Figure 4 .Input of Theme object discovery

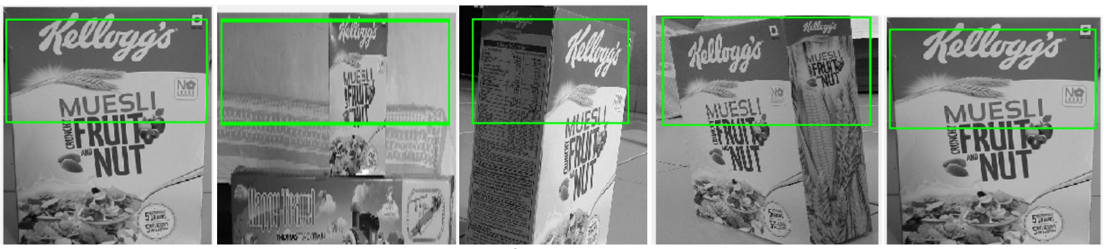

Figure 5.Output of Theme object discovery

Sr. No.	Extracted Theme Discovery	Dimensions	Feature count	Pruning Time (seconds)
1.		625x670	Initial -200 Final-146	10
2.		610x546	Initial -451 Final-338	17.31
3.		625x648	Initial -635 Final-442	24.92
4.		578x645	Initial -462 Final-317	31.6
5.		650x670	Initial -317 Final-233	34.17

VII. CONCLUSION AND FUTURE WORK

In this paper, the commonly appearing object in image set is recognized as by tracking of the frequently appearing object. It is skilful to handle theme object variations due to lighting, scale, color, and view of point. Here we are identifying only one theme object at a time. Our future work covers demonstrations on both, image collections and video sequences. Also covers identifying the multiple theme objects from the given collection of videos and images under the different theme object changes.

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