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Efficient Theme Discovery in Collection of Images

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Abstract: To acknowledge the existence frequently appearing object is called Theme discovery. Discovering common objects that appear frequently in a no. of images is challenging problem, due to
1. The appearance variations of the same common object and
2. The enormous computational cost involved in exploring the huge solution space, pruning procedure is 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 multilayer candidate pruning procedure is designed to accelerate the image data mining process. By searching the subimage of the highest commonness score in each image, we can locate and crop the theme object required.

Keywords: Image Data mining, Theme object Discovery.

I. INTRODUCTION

Fig.1.1. Examples of Theme object discovery

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 1.1 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.

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.

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.

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Fig.1.2 Multiple visual patterns

II. LITERATURE SURVEY

To discover similar visual primitives in videos and images, some existing task denote an image as a grid composed of visual primitives , such as corners, interest points, and image segments.[5]

Jun-Bin Yeh, Chung-Hsien Wu, and Sheng-Xiong Chang [1] presents a visual language model characterizes the temporal relation among the frames in a visual stroke. Detecting the object in a visual stroke is difficult and a textual term may generally match to respective word. The sentence based alignment corresponds to the language model-based temporal relation. The visual patterns are extracted from the bag-of-words represented from the main objects in the key frames of a visual stroke. The How Net knowledge base drives the textual terms to the textual concepts. The IBM model-1 is used to process the textual concepts and the visual patterns. David liu and Tsuhanchen presents a situation or model where there are multiple possible outcomes framework for discovering the thematic objects in video. The background can be covered with undity collection of things, the video can vary between different strokes, and the unrevealed objects can enter or leave the position at multiple times. These frameworks can be applied to a large-scale range of different objects and videos types. They had demonstrated excellent performances to method that drives global image Statistics and instant item set data mining techniques.

Hongliang Li and King Nga Ngan [6] 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 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.

Jianbo Shi and Jitendra Malik [3] proposed a novel approach for solving the grouping problem in vision. The theme of this paper is exactly to extract the global impression of an image. The complete dissimilarity between the different groups as well as the complete similarity within the groups is measured by normalized cut criterion.

Shalini N. and Sharada K. [4] proposed a paper where they are discovering thematic object in a video. This frequently appearances of object in a video are needful for object search and summarization of that object. Harris corner detection algorithm is referred to find the corner points of that object to be discovered. Video data mining process is used to recognize the common pattern that appears in that video.

III. SYSTEM MODEL

The below figure 2, explains the block diagram to identify the theme objects in videos and images [4]. 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.

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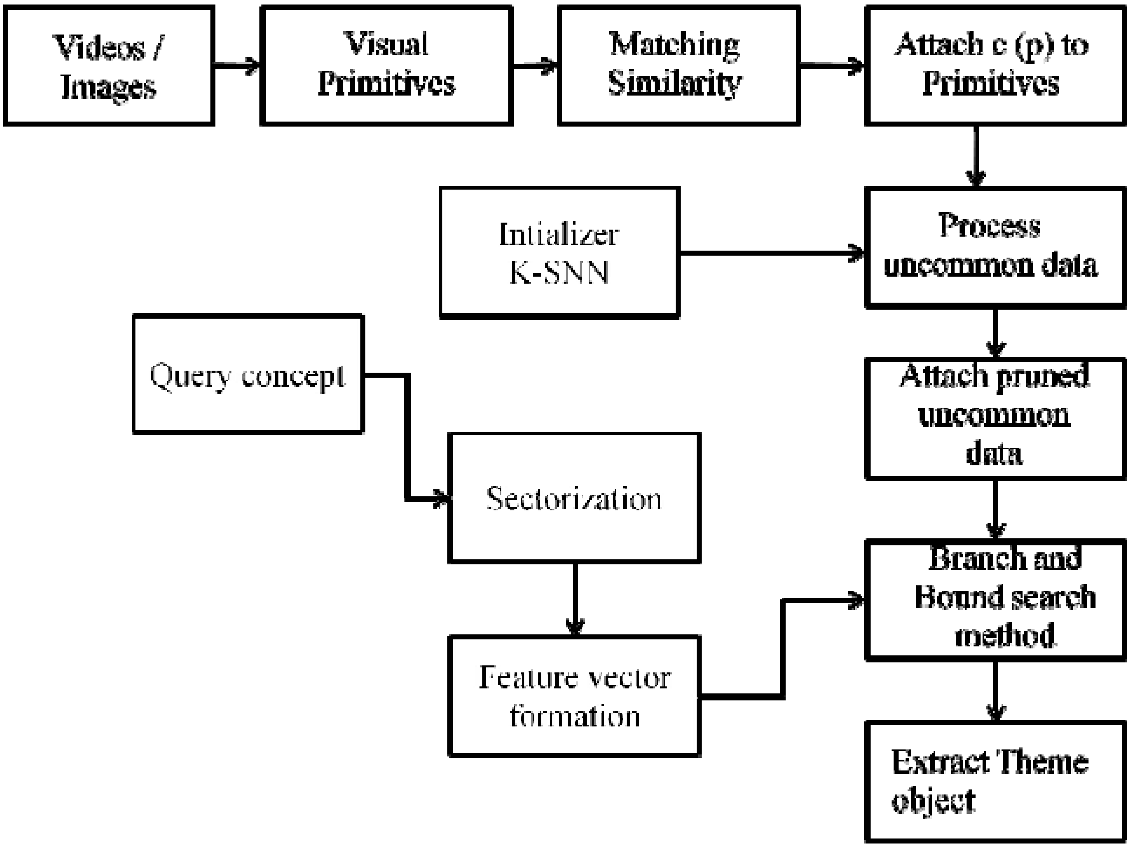

Fig2: System block diagram

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 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 $R \subset I$ that contains the most common primitives.

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.

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

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.

$$\mathbf{S_p} = \{\boldsymbol{G_q}: \boldsymbol{Sim}(\boldsymbol{G_p}, \boldsymbol{G_q}) > \boldsymbol{\theta}\} \qquad \textbf{(2)}$$

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, $D^L \subseteq \ldots\ldots \subseteq D^1 \subseteq D$ 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 τ is assigned as the negative vote value.

$$C(p) = \begin{cases} k^l & if\ p \in \{\mathcal{D}^l \setminus \mathcal{D}^{l+1}\}, 1 \leq l \leq L \\ \tau & \text{if } p \in (\mathcal{D} \setminus \mathcal{D}^1) \end{cases} \qquad (3)$$

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. $\boldsymbol{I}i$, we search for the bounding box R^* with the maximum commonness score.

$$R^* = \underset{R \subseteq I}{\operatorname{argmax}} \sum_{P \in R} C(P) = \underset{R \in \Lambda}{\operatorname{argmax}}\ F(R) \quad (4)$$

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Where F(R) $\sum_{P \in R} C(P)$ is the objective function and ^ denotes the candidate set of all valid sub images in $\boldsymbol{I}i$. 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.

V. CONCLUSION AND FUTURE WORK

In this paper, the commonly appearing object in an images from collection of images. 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 video sequences and image collections. 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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