Discovering Recurring Patterns in an Image

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***Abstract*—The project described in this report represents unsupervised method for discovering recurring patterns from a single view. A key contribution of this project is the formulation and validation of a joint assignment optimization problem where multiple visual words and object instances of a potential recurring pattern are considered simultaneously. This report mentions two methods with and without pre-knowledge of objects. First approach is achieved by segmentation techniques whereas the optimization is achieved by a greedy randomized adaptive search procedure (GRASP) with moves specifically designed for fast convergence. We have quantified systematically the performance of our approach under stressed conditions of the input (missing features, geometric distortions). We demonstrate that our proposed algorithm outperforms state of the art methods for recurring pattern discovery on a diverse set of real images.**

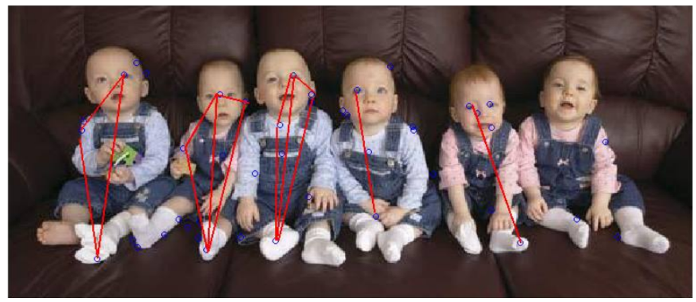


Fig. 1: Six instance recurring pattern, with unsupervised discovery of recurring pattern with partial patterns allowed

I. Introduction

Similar yet non-identical objects, such as animals in a herd, cars on the street, faces in a crowd or goods on a supermarket shelf, are ubiquitous. There has been a surge of interest in unsupervised visual perception of such near identical objects [1], echoing an observation that much of our understanding of the world is based on the perception and recognition of shared or repeated structures. To capture the recurrence nature within such patterns, we use the term recurring pattern to refer to the ensemble of multiple instances of a common visual object or object for short, which may or may not correspond to a complete physical object. As shown in Figure 1, each object of a recurring pattern is a geometric composition (red arcs) of visual words, where partial matching among the objects is permitted. The recognition of recurring patterns has applications in effective image segmentation [4], compression and super-resolution [2], retrieval [5] and organization of unlabeled data [7].

Two classic approaches for recurring pattern detection are: (A) pairwise visual-word-matching which matches pairs of visual words across all objects [7]; and (B) pairwise object-matching which matches feature point correspondences between a pair of objects [12, 5, 4]. Both of these methods are limited in that (1) Pairwise matching, though relatively simple, does not fully utilize all available information for optimal matching. (2) Visual word pair matching also suffers from missing feature points (low visual word recall rate), as shown by our quantitative evaluations (3) Whether it is better to match object-pairs or visual word-pairs is unknown in advance, and due to the lack of a global decision mechanism, current pairwise-matching systems do not afford flexible and adaptive switching between the two.

Approaches mentioned proposes an alternative joint- optimization framework for recurring pattern discovery by matching along both visual word and object dimensions simultaneously. Given the combinatoric nature of the problem, it further propose to use a Greedy Randomized Adaptive Search Procedure (GRASP)[13] for optimization. The major contributions are: (1) a novel object-visual word joint optimization framework (2) Using a novel segmentation technique to find the potential objects (3) an effective adaptation of GRASP for this joint optimization problem using stochastic moves specifically designed for fast convergence (4) a formal and explicit treatment of recurring patterns with potential missing/spurious feature points in real images.

II. Related Work

Recurring pattern discovery has been referred to in the literature as common visual pattern discovery [14, 5], co-recognition/segmentation of objects [15, 16, 4], and high order structural semantics learning [7]. [15, 17, 18] achieve unsupervised detection/segmentation of two objects in two separate images. Harshit and Anoop [25] use grouping of features on scale spaced pyramid. They extracted dense features and applied pairwise feature matching and pairwise patch matching. They further segmented the image regions by using watershed transformations. Yuan and Wu [14] use spatial random partitioning to detect object pair(s) from one or a pair of images. Cho et al. formulate the same problem as correspondence association solved by MCMC exploration

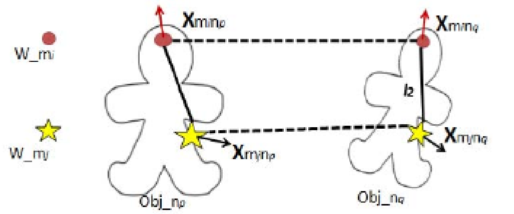
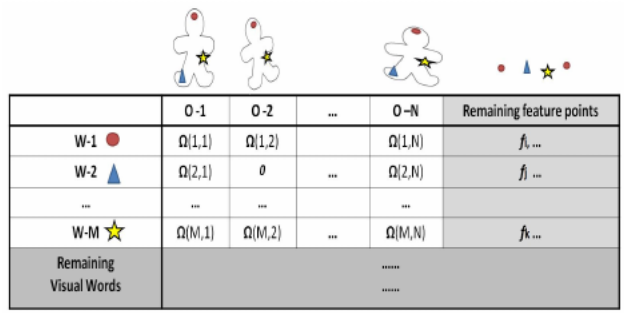


Fig. 2: The 4-tuple structure of smallest recurring pattern. Two shapes represents two potential visual objects, red and yellow points are visual features. W_{mi}, W_{mj} are the visual words containing the set of red and yellow features respectively.



	O-1	O-2	...	O-N	Remaining feature points
W-1	Ω(1,1)	Ω(1,2)		Ω(1,N)	f_i, ...
W-2	Ω(2,1)	0	...	Ω(2,N)	f_j ...
...	...	...		...	
W-M	Ω(M,1)	Ω(M,2)	...	Ω(M,N)	f_k ...
Remaining Visual Words	....				

Fig. 3: The 2D feature assignment matrix, where each row corresponds to a visual word and each column to a visual object.

[16, 17] and graph matching [3], respectively. [5] adopts graph matching to detect multiple recurring patterns between two images. To detect more than 2 recurring instances, Cho et al. generalize feature correspondence association under a many-to-many constraint and perform multiple object matching using agglomerative clustering [19] and MCMC association [4]. Both approaches are pairwise object matching based methods. Gau et al. [7] use the approach of pairwise visual word-matching, while assuming that visual words can be detected on all recurring instances (i.e. a 100% feature recall rate is required).

The method described in this report is published by Liu and Liu ,which differs from previous work in two significant ways: (1) it solves a simultaneous visual word-object assignment problem and (2) it explicitly and effectively deals with missing/spurious feature points in recurring patterns (feature recall rate from an image can be lower than 100%). We tried enhancing their methods by explicitly segmenting the potential objects in the image followed by pairwise visual word matching constructed by calculating the affinity between the features.

III. Approach Followed

We start with a formalization of the concept of a recurring pattern and its components (Fig. 2), followed by a step-by-step overview of our proposed computational framework (Fig. 3). The key technical steps are the selection and grouping of representative feature points into key visual words and the exploration of the structural consistency among their topology/geometry by using GRASP optimization to discover recurring patterns.

A. Formalization of Recurring Patterns

A visual object is defined as the potential region in the image which independently contains at least single recurring pattern in an image. A recurring pattern is defined such that it have at least two visual objects. Likewise each object of a recurring pattern is required to have at least two distinct visual words. A visual word is defined as the set of visual features which have the strong affinity. Thus, the smallest recurring pattern is conceptually a 4-tuple structure satisfying certain affinity constraints (Figure 2). The visual word distinctiveness requirement forces each object of a recurring pattern to have a compact representation (no nested recurrence of visual words within each object), thus qualifying it to serve as a structural-primitive for recurring pattern discovery. More importantly, this definition ensures the uniqueness of each recurring pattern while maximizing number of object instances. Mathematically, we construct a recurring pattern Ω as a 2D feature-assignment matrix where each row corresponds to a visual word and each column corresponds to a visual object (Figure 3), that is, $\Omega_{M,N}(m,n) = f_i$, where f_i corresponds to a feature point, $m = 1 \ldots M$, $n = 1 \ldots N$, and M and N are the number of visual words and objects, respectively. $\Omega_{M,N}(m,n)$ = 0 is used to indicate a corresponding feature point is missing.

B. Visual Word Extraction

Given a set of feature points F = $\{f_i | i = 1, \ldots K\}$, a visual word W is a subset of F such that all feature points in W share strong appearance similarity. These features are found by applying Scale Invariant Feature Transformation(SIFT). Let v_i be the normalized descriptor of f_i, such that $||v_i||_2$ = 1, we define a normalized affinity metric between features f_i , f_j as

$$A(i,j) = \frac{v_i^T v_j - avg\{v_p^T v_q | p,q = 1,2,\ldots K\}}{std\{v_p^T v_q | p,q = 1,2,\ldots K\}} \qquad (1)$$

and evaluate the intra-visual-word similarity of W by

$$s_W = \frac{1}{|W|} \sum_{i,j \in W} A(i,j) \qquad (2)$$

Starting with an initial assignment of $W = i, j$ where $A(i,j)$ is maximum among all feature pairs in F, we use a forward selection scheme where new feature points f_i are sequentially included into W that maximizes Eqn. 2. Once Eqn. 2 can no longer be increased, the growing of the current W stops and the extraction process then continues on F W to find the next visual word. Our visual word forward-selection

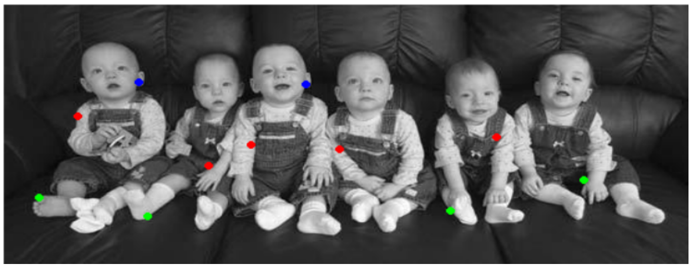


Fig. 4: Three different types of visual words are shown such that the intra-visual word affinity is maximum among all the SIFT features.

method differs significantly from K-means, in that we only extract inlier subsets of F to form a vocabulary of key visual-words for recurring patterns, while ignoring a considerable amount of background noise or outliers.

For efficiency, the affinity matrix A can be made sparse by setting $A(i,j) = 0$ for $A(i,j) < \tau$. In our experiments, we set $\tau = 2$ to remove feature pairs with distance that exceeds two-sigma. Given the sparsity of A, typically 30 $\tilde{2}$00 valid visual words can be extracted from a single image depending on the image content and resolution. Ideally, different feature points from the same visual word W should be present in the corresponding relative locations of all N objects of a recurring pattern, i.e. $N = |W|$. Due to image noise and distortion, we may only obtain $N^* < N$ inlier feature points for word W while getting $|W| - N^*$ outliers. To quantify the levels of such difficulty for recurring pattern discovery algorithms we define the visual-word recall RV W and precision PV W rates respectively as: $R_{VW} = N^*/N$, $P_{VW} = N^*/|W|$.

C. Recurring pattern formation

We propose two different approaches to use the visual words for matching.(1) Segmenting the potential objects and filling the rows in the 2D assignment matrix by pairwise visual word matching. We call this as the case where rows are unknown (2) We use the GRASP approach to find the geometric similarity between the features of different visual words proposed by Liu and Liu. We call this as the cases where both rows and columns are unknown.

1) Rows are unknown: We defined recurring pattern as the measure of affinity between visual words between at least two visual objects. For the 2D assignment matrix columns can be manually filled by the knowledge of potential objects. Various different approaches of object segmentation can be used to find the potential objects. This includes standard segmentation techniques like

- Watershed Transformations
- Region Growing
- Sliding Window Techniques, A small window is taken (say size 30x30) and the rows are filled by considering each sliding window as a visual object. These sliding windows can be overlapping or non-overlapping.

We then create 2D Match Matrix $M(i,j)$ where both rows and columns represents objects segmented and each value represents the number of common visual words occurring in objects i and j. Objects with the values greater than a threshold produces recurring pattern consisting of those visual words.

2) Both Rows and Columns are unknown: We use the second approach where the objects are also unknown. The idea is that the objects which will come in the 2D assignment matrix will definitely increase the geometric affinity of the features coming in the assignment matrix. Objects of a potential recurring pattern need to be supported not only by the appearance similarity of their matched feature-pairs from distinct visual words, but also by the geometric consistency of the spatial layouts of their corresponding visual words across objects. The geometric configuration of an entry (feature point) in $\Omega(m,n)$ is defined by $(x_{m,n}, s_{m,n}, \theta_{m,n})$, denoting the centroid, scale and rotation of the corresponding local image patch. The geometric affinity metric for a 4-tuple feature structure, the smallest recurring pattern (Fig. 2, is defined over two distinct visual words w_{mi} , w_{mj} and 2 objects o_{np} , o_{nq} as

$$g(m_i, m_j, n_p, n_q) = \exp(-\frac{\Delta_\theta^2}{2\sigma_\theta^2} - \frac{\Delta_s^2}{2\sigma_s^2}) \tag{3}$$

where Δ_s and Δ_s are normalized scale and angular distances measured by

$$\Delta_s = \frac{1}{2} \sum_{m=m_i,m_j} \frac{s_{m,n_q} - r.s_{m,n_p}}{\sqrt{r.s_{m,n_q} s_{m,n_p}}} \tag{4}$$

$$\Delta_\theta = \frac{1}{2} \sum_{m=m_i,m_j} \angle(\theta_{m,n_q} - \theta_{m,n_p} - \theta_0) \tag{5}$$

$r = d(x_{m_i n_q} x_{m_j n_q})/d(x_{m_i n_p} x m_j n_p)$, $\angle()$ is absolute angular distance, and θ_0 is the angle between line segment $x_{mi} n_p x_{m_j} n_p$ and $x_{mi} n_q x_{m_j} n_q$ (Fig. 2. Parameters σ , σ_s control the tolerance for shape deformation, both are set to 0.2 in the experiments. The overall geometric affinity of a candidate recurring pattern $\Omega(M,N)$ is then given by

$$G(\Omega_{M,N}) = \frac{1}{M.N - N_0} \sum_{\substack{m_i, mj=1\ldots M \\ n_i, nj=1\ldots N}} g(m_i, m_j, n_p, n_q) \tag{6}$$

where N_0 is the number of missing features. Finally, we can formalize recurring pattern detection as a joint optimization problem

$$\Omega^* = argmax_{\Omega,M,N} G(\Omega_{M,N}) \tag{7}$$

We set $g(m_i, m_j, n_p, n_q) = 0$ in case any of the features in the 4-tuple structure is missing ($\Omega(m,n) = 0$). This is later compensated for by a smaller normalization term $(M.N - N_0)$ (Eqn.6).

The optimization problem specified in Eqn.7 is NP-hard. We hereby adopt a Greedy Randomized Adaptive Search Procedure(GRASP) [13, 22]. This approach is commonly applied to solve difficult combinatorial optimization problems, although it has rarely been applied to computer vision problems in the past.

3) GRASP framework: GRASP is a multi-start meta-heuristic algorithm for solving combinatorial optimization problems. Each iteration consists of two phases: (1) random initialization of a feasible solution: since GRASP seeks a local optimum for each random initialization, it is important that a variety of initial states be generated to fully explore the solution space. We randomly select 2 visual words for initialization in our experiments.(2) local greedy optimization: We define 5 basic local moves to construct a neighborhood-traversal system in the solution space: **(a)add a visual word, (b)add an object, (c)modify a single feature point, (d)remove a visual word and (e)remove an object.** These correspond to adding/removing a row/column or modifying an entry in the assignment matrix $\Omega_{M,N}$ (Fig. 3). We apply stochastic greedy moves, which means that all candidate moves are evaluated and we randomly select among the top 3 moves that improve the objective function. This approach lets us explore a variety of local optima through different randomized paths during the expansion of Ω.

4) Local Moves: For all moves described below, only moves that improve Eqn. 7 are valid

1. Add-a-visual-word: $\Omega_{M,N} \rightarrow \Omega_{M+1,N}$. Let a new word candidate contain $n = 1, \ldots N$ feature points $(W|_{M+1}| = N)$. The assignment of N points to $N^{'}$ objects can be solved using graph matching by defining an $NN^{'} - by - NN^{'}$ affinity matrix U , with each entry $U(i, j)$ indicating the co-assignment affinity of n_i to n_i and n_j to n_j , evaluated by:

$$U(i, j) = \sum_{m=1}^{M} g(m_i, m_j, n_p, n_q) \quad (8)$$

The assignment of features in the new word W_{M+1} to each object can be determined from the optimal binary indicator vector: $x^* = argmax(x^T U x)$, subject to an additional 1- to-1 feature allocation constraint. Eqn.8 reflects one distinctive characteristic of our approach: we are looking for a consistent matching between the new candidate W_{M+1} and all existing visual words $W_m, m = 1, \ldots M$, instead of only isolated pairwise matches. Although the graph matching problem with 1-to-1 constraints is NP-hard, our sub-problem is of small scale, and can be handled by state-of-the-art empirical graph matching methods (e.g.[3]).

2. Add-an-object: $\Omega_{M,N} \rightarrow \Omega_{M,N+1}$. Any remaining feature points f_i in $W_m, m = 1, \ldots M$ can start a new column $\Omega_{m,N+1}$ to propose a new candidate object. We then fill in the rest of column $N + 1$ by independently examining leftover feature points in W_m as well as missing features $\Omega_{m,N+1} = 0$, for $m = 1, \ldots, M$, and optimizing the affinity between the new object $N+1$ and all existing objects: $\Omega(m, N + 1)^* = argmax(g(m, m, n, N + 1))$.

3. Modify-feature-entries enumerates and replaces all entries in $\Omega_{M,N}(m, n)$ with the remaining feature points in the same words Wm or $\Omega(m, n) = 0$.

4/5. Remove-a-visual-word/object removes a row or column from the feature matrix $\Omega_{M,N}$.

D. GRASP Procedure

Repeat: randomly initialize the feature matrix Ω_{MN}
Repeat: sequentially apply moves 1-5
Until: no valid moves increase G in Eqn. 7
Until: maximum number of re-initializations reached

IV. Experiments and Results

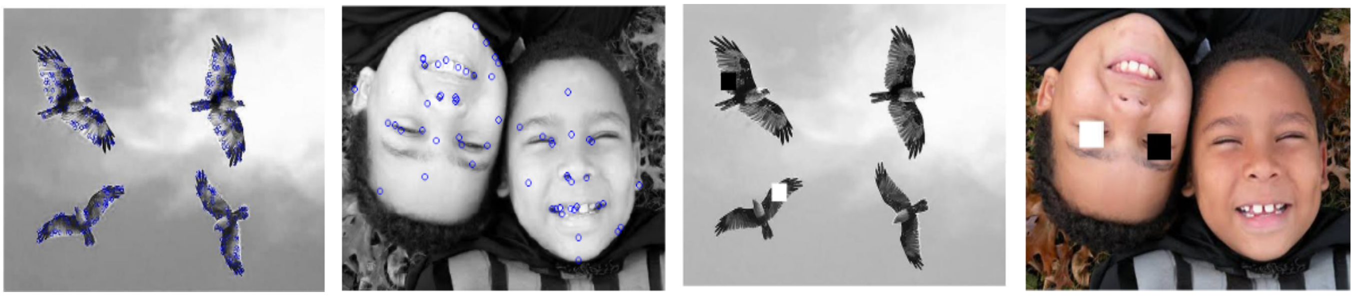
Experiment is executed on real image data-set containing different textured images.Although the GRASP optimization requires repeated calculation and evaluation of candidate moves, most calculation involves the geometric affinity estimation of Eqn. 3. These affinities can be pre-computed on all 4-tuple combinations, and the main computation during optimization is only the summation and indexing from Eqn. 7. The algorithm is implemented using Matlab with no compiler optimization and was run on a 2.6GHz, i7 CPU. To evaluate the repeatability and variance of GRASP initialization, we performed 30 random initializations for GRASP, and observed on average that 29% of the attempts end up with equivalently high R_{out} /P_{out} performances. Figure 5 and Figure 6 are the sample output results of the algorithm.

V. Discussions

Fig 5(a), 5(b) shows the recurring pattern in the image which contains non-occluded objects as the segmentation techniques give good results in such cases. We have used watershed transformation as the segmentation techniques and found out the results which are very close to the results of the second approach proposed by Liu and Liu through GRASP Procedure.

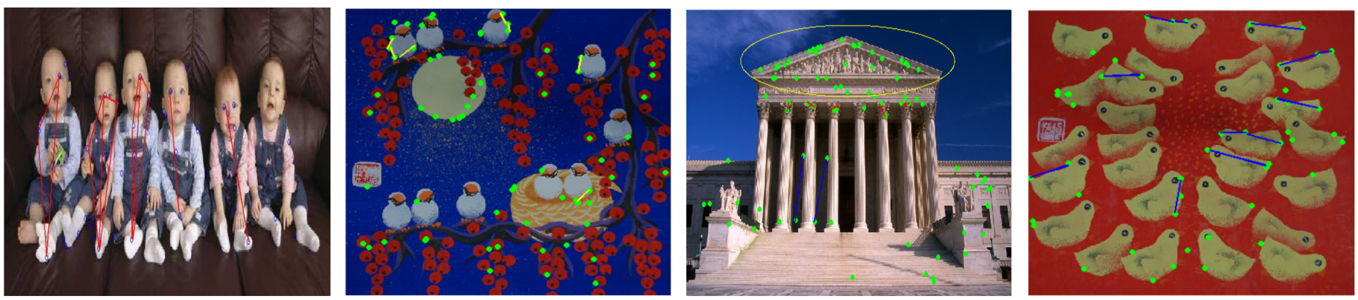
Although both approaches give close results but both has some pros and cons. In pairwise visual word matching approach proposed in this report, pattern is discovered from a part of the image and not from whole of the image. Objects of interest are those which are segmented by the segmentation techniques. This method strongly depends upon the segmentation technique used for knowledge of the objects whereas in Joint Optimization approach, no prior knowledge of objects are needed. Greedy approach itself bring the potential objects which are going to increase the overall affinity in the 2D feature assignment matrix. It is the mixture of the pairwise visual word and pairwise object matching(takes care of the intra-word and inter-word affinity/similarity).

Generalization to multiple patterns/images: Although the description of our approach (Section 3) has focused on discovering a single recurring pattern in a single image, we can generalize it to multiple patterns/images. We treat multiple images as one huge image and impose an extra constraint that forbids feature points across different images to be associated to form an object. Multiple recurring patterns are discovered



(a) (b) (c) (d)

Fig. 5: Fig (a), (b) represents Recurring pattern results after segmenting objects(Watershed Transformation) and pairwise visual word matching. Fig (c) and (d) represents recurring pattern results using sliding window techniques.



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 6: Sample output of our algorithm. Object recall and precision rates are 92% and 96% respectively. Average objects per recurring pattern is 10. Worth noting: top-center painting contains only all the chicks facing to the left while the rotated object instances in the top-right image are found completely. This reflects that at object-level the instances are shift- and rotation-invariant yet not reflection invariant.

with a recursive greedy approach: each time a pattern is discovered, all its associated feature points are removed and the discovery process restarts. Fig 6(b), 6(c), 6(e) are the examples of the multiple recurring patterns in the single image. The recurring pattern also depends upon the initialization visual words and the number of initializations. In Fig 6(b), there are multiple patterns detected, one is the top and other one are the pillars. The top pillar is the false recurring pattern from the ground truth image, due to the random initialization of the pattern, whereas Fig 6(d) is the case of the number of initializations. Difference can be seen in Fig 7(a) and 7(b). In one initialization, there are more number of false positives. These false positives are calculated by the ground truth images obtained from [19]

VI. Applications

As a byproduct of recurring pattern discovery, we can directly match and register (visual word by visual word) all instances found in a recurring pattern, which can be further used for regularity evaluation and categorization. Fig. 9(a) shows a detected recurring pattern with an average pairwise normalized correlation (APNC) score of 0.86 after pattern registration, suggesting high likelihood of a doctored photo of crowds, as compared with an APNC score of a small group of llamas at 0.64 (Fig. 8(b)). Using the average object geometry deformation and the APNC score of a recurring pattern to

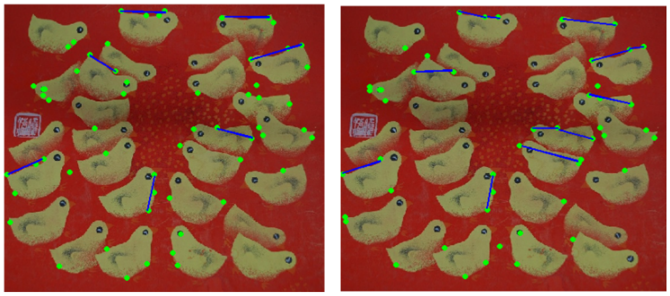


Fig. 7: The improvement in the results depends upon the number of re-initializations. Left side figure is the result of only one initialization whereas right figure is the result of three random re-initializations.

approximate its quantified regularity in a 2D space, we observe a striking relation between recurring pattern categories and their geometry/photometry deviation from perfect regularity. We thus see much potential of our unsupervised recurring pattern discovery algorithm to contribute to object recognition and pattern categorization.

VII. Limitations

We used segmentation techniques in the method to find the prior objects which can contain the recurring pattern. These segmentation techniques are of utmost importance. But they can not be generalised and cannot give a general solution. We want a method which can be generalised to all images containing occluded and non-occluded objects in the image.

In sliding window approach common region between the two windows increases the match and therefore appears as a recurring pattern candidate giving false results. Although this problem can be solved by taking non-overlapping windows,but that might lend up in incomplete results. Moreover, the threshold we define for pairwise visual word matching cannot be generalised. It depends upon the image and is problem specific.

Second technique which we use is Joint Optimization is robust enough to solve all these problems but it has some string limitations. Since we are iterating to find the maximum for the objective function, we might end up in local maximum. This can be solved by re-initializations but the number of re-initializations is problem specific. Liu and Liu find out that the solution is converging and will lead to the correct results after fixed number of re-initializations.

VIII. Conclusion

We enhanced the novel adaptation of GRASP and demonstrated its effectiveness through extensive evaluations on a variety of difficult real-world images. Compared to state-of-the-art approaches, our method achieves superior object-level precision and recall rates. Although GRASP is not theoretically guaranteed to reach the global optimum compared to MCMC, practically it terminates a bad initialization quickly and thus explores the solution space more efficiently. The potential applications of an automated recurring pattern discovery tool are enormous, ranging from image registration, segmentation, people/product counting, surveillance to saliency perception.

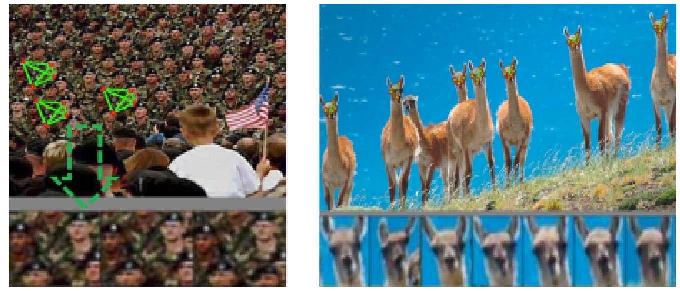


Fig. 8: (a) a doctored photo with found recurring pattern: APNC score = 0.86; (b) an example of registered recurring pattern of a group of llamas with an APNC scores of 0.64, indicating their inherent and statistically significant category differences.

Acknowledgment

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