Real Time Object Tracking with Sparse Prototypes

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Abstract

Sparse representation (compressive sampling) has achieved impressive results in object tracking by looking for the best candidate with minimum reconstruction error using the target template. However, it may fail in some circumstances such as illumination changes, scale changes, the object color is similar with the surrounding region, and occlusion etc., in addition, high computational cost is required due to numerous calculations for solving an l_1 norm related minimization problems. In order to resolve above problems, a novel method is introduced by exploiting an accelerated proximal gradient approach which aims to make the tracker runs in real time; moreover, both classic principal component analysis algorithm and sparse representation schemes are adapted for learning effective observation model and reduces the influence of appearance change. Both qualitative and quantitative evaluation demonstrate that the proposed tracking algorithm has favorably better performance than several state-of-the-art trackers using challenging benchmark image sequences, and significantly reduces the computing cost.

Keywords: Sparse prototypes, Object tracking, Real time, Appearance model

1. Introduction

Visual tracking has long been an important research topic in the computer vision field as it is widely applied in the automated surveillance, vehicle navigation, automatic object identification and target tracking for robots [1]. Although many different tracking methods have been developed, it remains a challenging task due to appearance change caused by extrinsic and intrinsic factors such as sophisticated object shapes or complex motions, partial occlusions, pose and illumination changes.

Recently, lots of methods have been successfully applied to object tracking and can be summarized into two categories: discriminative and generative approaches. Discriminative methods treat the tracking problem as a classification problem, which aims to segment the target from the background [2, 3]. So it considers the information of both the target and background. Some trackers combined a set of weak classifiers into a strong one [4], adopting an online boosting method to update discriminative features [5] or learning a large number of positive and negative samples for tracking. Generative methods formulated tracking by establishing the appearance model of the target. In order to develop effective models, several particularly factors should be considered. First, to adapt to the target appearance variations caused by pose change and illumination change, the target model needs to be updated online [6, 7]. In addition, Wu, *et al.*, [8] presented a novel Blur-driven tracker framework for tracking motion-blurred targets. Experimental results showed that discriminative models perform better when the training set size is large while generative models achieve higher generalization if limited data is available [9–11].

Benefitting from less cost of generative model, sparse representation techniques [12, 13], also known as compressed sensing or compressive sampling, for finding a sparse solution through solving an l_1 -regularized least problem, plays a critical role in both mathematics and applications such as visual tracking. Mei, *et al.*, [12, 14, 15] employed the sparse representation of the object as the appearance model and then obtained the tracking target by solving the l_1 minimization problem, and achieved some ideal results but failed when there were similar objects in the scene. To further improve the method, they introduced non-negativity constraints and dynamically updated the target templates [16, 17]. However, most sparse representation used the holistic model to denote the appearance model and cannot handle distracters and partial occlusion accurately.

Similarly with sparse representation, but combined with classic principal component analysis (PCA) algorithm and online object tracking algorithm, an robust generative tracking algorithm with an adaptive appearance model is proposed called sparse prototypes (SP), which handles partial occlusion built into the same framework of the online object tracker [18]. With the intuition that the appearance of a tracked target can be sparsely represented, therefore, finding a sparse which approximates the template subspace is necessary because it is effective in dealing with pose, illumination and scale variation as well as appearance change. Moreover, this paper also aims at developing a more efficient tracker in real time. The main contribution of this paper is to introduce a very fast numerical method [19] to solve the minimization problem [18], which is further reorganized, so that the proposed numerical method could be combined into the SP tracker and make it run in real time.

2. Related Work

In recent years, there has been a large amount of literature on target tracking problems, and studies which related to our work are summarized in this section. Generally speaking, there are several major issues in target tracking, such as appearance caused by in-plane rotation, scale illumination, poses change, partial occlusion and so on. Several experimental results demonstrate that PCA subspace representation with online update is effective in dealing with some of these issues except partial occlusion [20]. The Incremental Visual Tracking (IVT) [21] method introduced an online update approach for efficiently learning and updating a low dimensional PCA subspace representation of the target object, which is sensitive to partial occlusion.

However, there might be a drift by using the method of direct template update, so Viola, *et al.*, [22] introduced Multiple Instance Learning (MIL) into visual tracking to address this problem. Moreover, the l_1 tracker [15] included a sparse representation of trivial templates so that its sparse linear combination can present the occlusions and image noise in the target. In this approach, the sparse representation is obtained via solving a l_1 -norm related minimization problem and the l_1 tracker turns out to be too slow to be a real time tracking method.

In this paper, advantages of both subspace method and sparse representation method are combined effectively to solve the partial occlusion problem. In addition, a fast numerical method for solving the l_1 -norm related minimization problem is also applied to improve the method's computational rate. The experimental results show the proposed method has a good robustness against pose changes and illumination changes while at the same time achieving great running time efficiency. This paper is organized as follows: a sparse prototype is introduced in Section 3; the method of real-time object tracking is proposed in Section 4; experimental results and analysis are given in Section 5, and this paper is concluded with remarks in Section 6.

3. Introduction to Sparse Prototypes

Sparse prototypes is closely related to the $l1$ tracking method [15, 18], a brief review on the $l1$ tracker within the particle filter framework proposed in reference [18, 19, 21] will make it is easy to state the sparse prototypes. Particle filtering [23] is to find a set of transmissions in the state space representation of a random sample to approximate the probability density function, instead of using the sample mean calculus, and then get the system state minimum variance estimation process, these samples are called as “particles” vividly, and therefore called particle filter. Then the representation is used in the particle filter framework [18] for object tracking. Specially, for frame at t , we set the state variable x_t which indicates the position and shape information, with $z_{1:t}$ to describe the observed value of the target from the first frame to the frame t . The state prediction equation and status update equations for the particle filter are as follows:

$$p(x_t | z_{1:t-1}) = \int p(x_t | x_{t-1}) p(x_{t-1} | z_{1:t-1}) dx_{t-1} \quad (1)$$

$$p(x_t | z_{1:t}) = \frac{p(z_t | x_t) p(x_t | z_{1:t-1})}{p(z_t | z_{1:t-1})} \quad (2)$$

Where $p(z_t | x_t)$ denotes the observation likelihood from the state at time t . It is practically intractable to calculate the above probability distribution directly, so the posterior $p(x_t | z_{1:t})$ is approximated by finite samples $\{x_t^1, x_t^2, \dots, x_t^N\}$ with different weights $\{w_t^1, w_t^2, \dots, w_t^N\}$ where N is the number of samples and $\delta(x_t - x_t^i)$ is Dirac delta function. The samples are generated by an approximated equation

$$p(x_t | z_{1:t}) \approx \sum_{i=1}^N w_t^i \delta(x_t - x_t^i) \quad (3)$$

And the weights are updated by:

$$w_k^i = w_k^{i-1} \frac{p(z_t | x_t^i) p(x_t^i | x_{t-1}^i)}{q(x_t^i | x_{t-1}^i, z_t)} \quad (4)$$

In the case of the bootstrap filter $q(x_t^i | x_{t-1}^i, z_t) = p(x_t | x_{t-1})$ and the weights become the observation likelihood $p(z_t | x_t)$.

According to the weights distribution, in each step, samples are re-sampled to generate new sample set with equal weights in case the weights of some particles keep increasing or fall into the degeneracy case.

The sparse representation aims at calculating the observation likelihood $p(z_t | x_t)$, and some researchers have proposed an algorithm [12, 16, 17] by casting the tracking problem as finding the optimal patch with sparse representation and handling partial occlusion with trivial templates, then the patch is normalized and reshaped to a one-dimensional vector y which is formulated as a target candidate. This can be viewed as a minimum error reconstruction through a regularized $l1$ minimization function with non-negativity constraints:

$$\min_c \frac{1}{2} \|y - Bc\|_2^2 + \lambda \|c\|_1 \quad (5)$$

Where B is composed of target template set and trivial template sets, while c is composed of target coefficient and trivial coefficient. The main differences compared with sparse representation lie in a different target template model. For target tracking, we model object appearance with PCA basis vectors and some trivial templates. The sparse prototypes representation model is then:

$$y = Dz + e = [D \quad I] \begin{bmatrix} z \\ e \end{bmatrix} \quad (6)$$

Where I is identity matrix and is a trivial template set, y indicates an observation vector, D represents a column basis vectors, z represents the coefficients of basis vectors, and e denotes the error term. The prototypes in this formulation consist of a set of PCA basis vectors and a set of trivial templates. We solve Eq. (6) by

$$\min_a \frac{1}{2} \|y - Ba\|_2^2 + \lambda \|a\|_1 \quad (7)$$

Where $B = [D, I, -I]$ is composed of target template set D and trivial template sets I and $-I$.

Finally, the observation likelihood is derived from (see reference [18] and the references therein):

$$p(y_t^i | x_t^i) = \frac{1}{\Gamma} \exp[-(\|w^i \circ (y_t^i - Dz_t^i)\|_2^2 + \beta \sum (1 - w^i))] \quad (8)$$

Where $p(y_t^i | x_t^i)$ indicates not only the reconstruction of Eq.(7), but also any pixel as being occluded. z is obtained by solving the Eq.(7), α is a constant controlling the shape of the Gaussian kernel, r is a normalization factor, then the optimal state x_t^* of frame t obtained by:

$$x_t^* = \arg \max_{x_t^i \in S_t} p(z_t | x_t^i) \quad (9)$$

In addition, the update of observation model is adopted [18] for handling appearance change of a target object for visual tracking.

4. Real Time Object Tracking

Through the narrative of the front sections, the SP algorithm can be seen as an optimization problem, which is to solve the formula (7). The proposed method for solving the $l1$ minimization problem (7) based on the accelerated proximal gradient approach [19, 24] is given in algorithm 1.

The minimization model can be converted to the APG method:

$$\min_a F(a) + G(a) \quad (10)$$

As long as $F(a)$ is a convex function with Lipchitz [19] continuous gradient, as the same time, $G(a)$ is a non-smooth but convex function. Within $K = O(\sqrt{L/\varepsilon})$ iterations, x_k achieves ε -optimality such that $\|x_k - x^*\| < \varepsilon$, where x^* is one minimized parameter of Eq. (10). For Eq. (7), it is completely equivalent to the minimization problem as below:

$$\arg \min_a \frac{1}{2} \|y - Ba\|_2^2 + \lambda \mathbf{1}_T^T a + \|a\|_1 + \mathbf{1}_{R_+^n a} \quad (11)$$

In which $\mathbf{1} \in R^n$ represent the vector with all entries are equal to 1, and $\mathbf{1}_{R_+^n a}$ can be defined:

$$\mathbf{1}_{R_+^n a} = \begin{cases} 0 & a \geq 0 \\ +\infty & otherwise \end{cases} \quad (12)$$

Then we assume that:

$$F(a) = \frac{1}{2} \|y - Ba\|_2^2 + \lambda \mathbf{1}_T^T a \quad (13)$$

$$G(a) = \|a\|_1 + \mathbf{1}_{R_+^n} a$$

Algorithm 1: our tracker

1. Initialization
 2. Load the image sequences
 3. Candidate Sampling
 4. Adopt *PCA_LI* to acquire templates set
 5. Solving the minimization Eq.(7) via algorithm 2
 6. Calculate observation likelihood via Eq.(8)
 7. Obtain the optimal candidate by Eq.(9)
 8. Collect samples for model update
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To solve the minimization Eq.(7), algorithm 2 has been proposed as follows:

Algorithm 2: Real time numerical algorithm for solving the minimization (7)

1. For a given nonnegative vector λ , choose $x^0 = x^1 \in \Re^n$, $t^0 = t^{-1} = 1$.
For $k = 0, 1, 2, \dots$, generate x^{k+1} from x^k according to the following iteration which would be convergence eventually.
 2. $y_k := x_k + \frac{t_{k-1} - 1}{t_k} (x_k - x_{k-1})$
 3. $g_k := y_k - \nabla f(y_k) / L$,
 4. $x_{k+1} := \max(0, g_k)$
 5. $t_{k+1} := \frac{1 + \sqrt{1 + 4(t_k)^2}}{2}$
-

Then the real time object tracking algorithm can be solved through the above steps.

5. Experiments

The proposed algorithm is implemented by using the software Matlab and achieves about average 23 frames per second with 400 particles on a PC with Intel E7500 CPU (2.93GHz). The datasets are available on: http://faculty.ucmerced.edu/mhyang/project/tip13_prototype/TIP_12-SP.htm, http://faculty.ucmerced.edu/mhyang/project/cvpr12_jia_project.htm.

5.1 Experimental settings

Target of interest in the first frame position will be set manually and then automatic tracking is possible. The object is normalized to 32×32 pixels and 16 eigenvectors are used in all experiments for PCA representation. The number of templates for the sparse representation is 10. With our algorithm 2, 600 particles are used and the maximum number of iterations is set to 20, our tracker is updated every 5 frames and we assume the regularization constant λ as 0.05 in all experiments.

5.2.2. Illumination Change: For the car4 sequence, as shown in Figure 4 and Figure 5, there will be dramatic illumination changes when the vehicle passes through the shadows of the trees or the overpass. The MIL methods are less effective when tracking the car, and the tracking results even drift away from the target because of the illumination variation. In addition, it is more challenging for object tracking in the car11 video, because the target object is small with varying illumination and low contrast, and its appearance changes in different poses and scales by a dynamic camera. Both our methods and PCA methods can track the target effectively while others have serious drift phenomenon. This may be caused by the changes in appearance of the object, which can be well approximated with fixed posture subspace. Additionally, from the above results, trackers, such as MIL tracker, *l1* tracker and VTD tracker do not adapt to different scales or in-plane rotations especially dramatic lighting changes.

5.2.3. Cluttered background: When it comes to lemming sequence, the most prominent and challenging issues is the heavy occlusion in a cluttered background as well as changes of scales and poses as shown in Figure 6 and Figure 7. The MIL and our methods perform well.

5.2.4. Abrupt motion: In the Deer video, there is a huge challenge about the varying appearance caused by the motion blur as well as the fast motion. The tracking results are shown in Figure 8 and Figure 9. For the deer sequence, our tracker and VTD tracker perform better than other methods due to the re-initialization update model. The MIL tracker is able to track the object in some frames after drifting away caused by the similar surrounding background as the deer reappears at the same location in the image. But it failed later due to the motion blur. The PCA and $l1$ trackers are less effective and drift away from the deer with the repetitive motions. These results indicated the importance of a proper update appearance model and it is very difficult to predict the locations of the object when the fast motion occurs as in the car11 sequence which exist low contrast, dynamic camera motion as well as changing appearance caused by different poses and scales.

5.3. Quantitative Comparison with Other Methods

Two forms of assessment methods are employed to quantitatively show the performances of the proposed tracker. Figure 10 and Figure 11 presents the overlap rate and average center error of each tracking algorithm for all the sequences.

Table 1 and Table 2 summarize the results in terms of the average tracking overlap and error, which shows that our method achieves the lowest tracking errors.

overlap	PCA	<i>LI</i>	VTD	MIL	Ours
Car4	0.92	0.84	0.73	0.34	0.92
Car11	0.81	0.44	0.43	0.17	0.81
Caviar1	0.28	0.28	0.83	0.25	0.89
David Indoor	0.71	0.63	0.53	0.45	0.80
Lemming	0.18	0.13	0.35	0.53	0.75
Occlusion	0.85	0.88	0.77	0.59	0.91
Deer	0.22	0.04	0.58	0.21	0.61
Singer1	0.66	0.70	0.79	0.33	0.82
Average	0.58	0.49	0.63	0.36	0.81

In addition, the success rate is evaluated through the overlap rate which is defined by the PASCAL VOC [26] criterion if given the tracking result of each frame R_T , the corresponding ground truth R_G and $score = \frac{area(R_T \cap R_G)}{area(R_T \cup R_G)}$ area. The tracking results are regarded as being valid when the score is over 0.5. The average overlap rate of our tracker is 0.82 while the highest is 0.61 at present.

Average center	PCA	<i>LI</i>	VTD	MIL	Ours
Car4	2.87	4.08	12.29	60.10	3.03
Car11	2.11	33.25	27.05	43.47	2.17
Caviar1	45.25	119.93	3.91	48.50	1.67
David Indoor	3.59	7.63	13.55	16.15	3.65
Lemming	93.38	184.85	86.89	25.58	9.1457
Occlusion1	9.18	6.50	11.13	32.26	4.70
Deer	127.47	171.47	11.92	66.46	8.53

Singer1	8.48	4.57	4.06	15.17	4.75
Average	36.54	66.54	21.35	38.46	4.71

Consistent with the appearance updating in reference [18], if the object is well tracked and the occlusion rate is small, the tracking result is then used to update the observation model directly. We give the results using only Eq. (8) with the occlusion map in Table 1 to demonstrate how the occlusion map facilitates the object tracking and the observation update. The results show that our algorithm can effectively predict the occlusion maps and further improve the tracking results in terms of both overlap rate in Table1 and the center location error in Table 2. Overall, the minimum error rate and maximum overlap rate in all the sequences show that our algorithm has the best performance compared with several other the-state-of-the-art trackers on challenging benchmark image sequences by considering more factors.

5.4. Computational Complexity

Performance evaluation methods above show the proposed method is more accurate and robust in most challenging sequences. In addition, it is more efficient, because it reduces several orders of magnitude for the computational complexity compared with the other algorithms. We have analyzed the time complexities of some algorithms previously mentioned, for example, the complexity of the *II* tracker is $O(d^2 + dk)$, the sparse representation tracker has $O(ndk)$ complexity [18], but for the SP tracker in this paper, the complexity is $O(\sqrt{d/k})$, which is consistent with the analysis of accelerated proximal gradient algorithm [19].

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6. Conclusion

We introduced a novel fast object tracking approach by proposing a sparse prototype representation and a new accelerated proximal gradient approach. The method in this paper exploits both classic principal component analysis algorithm and recent sparse representation to obtain the observation model and uses an accelerated proximal gradient approach to locate the target more accurately and faster. It does not only adapt the tracker to account for the object appearance change but also handles the occlusion caused by similar objects or distinct. Comparing with several other the-state-of-the-art methods, the experimental results on challenging benchmark image sequences demonstrated both the effectiveness and efficiency of the proposed method. As the proposed algorithm utilized representation scheme, we will optimize it for more effective object tracking and extend it to object recognition.

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References

- [1] Y. Yuanlong, G. K. I. Mann and R. G. Gosine, "A single-object tracking method for robots using object-based visual attention", *International Journal of Humanoid Robotics*, vol. 4, (2012), pp. 1-36.
- [2] M. Heber, M. Godec, M. Ruther, P. M. Roth and H. Bischof, "Segmentation based tracking by support fusion", *Computer Vision and Image Understanding*, vol. 117, (2013), pp. 573-586.
- [3] W. Brendel and S. Todorovic, "Video Object Segmentation by Tracking Regions", *IEEE 12th International Conference on Computer Vision (ICCV)*, (2009) September 27 - October 4, pp. 833-840, Kyoto, Japan.
- [4] S. Avidan, "Ensemble tracking", *IEEE Transaction on pattern analysis and machine intelligence*, vol. 2, no. 29, (2007), pp. 261-271.
- [5] H. Grabner and H. Bischof, "On-line boosting and vision", *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition(CVPR)*, (2006) June 17-22, pp. 260-267, New York, USA.
- [6] Y. Wu, J. Lim and M. H. Yang, "Online Object Tracking: A Benchmark", *2013 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, (2013) June 23-28, pp. 2411-2418, Portland, USA.
- [7] R. Yao, Q. Shi, C. Shen, Y. Zhang and A. Hengel, "Part-based Visual Tracking with Online Latent Structural Learning", *2013 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, (2013) June 23-28, pp. 2363-2370, Portland, USA.
- [8] Y. Wu, H. Ling, J. Yu, F. Li, X. Mei and E. Cheng, "Blurred Target Tracking by Blur driven Tracker", *2011 IEEE International Conference on Computer Vision (ICCV)*, (2011) November 6-13, pp. 1100-1107, Barcelona, USA.
- [9] J. A. Lasserre, C. M. Bishop and T. P. Minka, "Principled hybrids of generative and discriminative models", *2006 IEEE Computer Society Conference on Computer Vision Pattern Recognition (CVPR)*, (2006) June 17-22, pp. 87-94, New York, USA.
- [10] A. Y. Ng and M. I. Jordan, "On discriminative versus generative classifiers: A comparison of logistic regression and naive bayes", in *Proc. Adv. Neural Inform.*, (2002), pp. 438-451.
- [11] W. Zhong, H. Lu and M. H. Yang, "Robust object tracking via sparsely based collaborative model", *2012 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, (2012) June 16-21, pp. 1838-1845, Providence RI, USA.
- [12] B. Liu, J. Huang, L. Yang and C. A. Kulikowski, "Robust tracking using local sparse appearance model and k-selection", *2011 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2011) June 20-25, pp. 1313-1320, Providence RI, USA.
- [13] B. Liu, L. Yang, J. Huang, P. Meer, L. Gong and C. A. Kulikowski, "Robust and fast collaborative tracking with two stage sparse optimization", *11th European Conference on Computer Vision*, (2010) September 5-11, pp. 624-637, Heraklion, Crete, Greece.
- [14] J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry and Y. Ma, "Robust face recognition via sparse representation", *IEEE Transactions Pattern Analysis and Machine Intelligence*, vol. 1, no. 31, (2009), pp. 210-227.
- [15] X. Mei and H. Ling, "Robust visual tracking using l_1 minimization", *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, (2009) September 27-October 4, pp. 1436-1443, Kyoto, USA.
- [16] X. Mei, H. Ling, Y. Wu, E. Blasch and L. Bai, "Minimum error bounded efficient l_1 tracker with occlusion detection", *2011 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, (2011) June 20-25, pp. 1257-1264, Providence RI, USA.
- [17] X. Mei and H. Ling, "Robust Visual tracking and vehicle classification via sparse representation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no. 33, (2011), pp. 2259-2272.
- [18] D. Wang, H. Lu and M. H. Yang, "Online Object Tracking with Sparse Prototypes", *IEEE transactions on image processing*, vol. 1, no. 22, (2013), pp. 314-325.
- [19] Z. Shen, K. C. Toh and S. Yun, "An Accelerated Proximal Gradient Algorithm for Frame Based Image Restoration via the Balanced Approach", *SIAM J. Imaging Sciences*, (2011), pp. 573-596.
- [20] D. Wang, H. Lu and Y. W. Chen, "Incremental MPCA for color object tracking", *20th International Conference on Pattern Recognition (ICPR)*, (2010) August 23-26, pp. 1751-1754, Istanbul, Turkey.
- [21] D. Ross, J. Lim, R. S. Lin and M. H. Yang, "Incremental Learning for robust visual tracking", *International Journal of Computer Vision (IJCV)*, (2008), pp. 125-141, USA.

- [22] P. A. Viola, J. C. Platt and C. Zhang, "Multiple instance boosting for object detection", In Advances in Neural Information Processing Systems, vol. 18, (2006), pp. 1417-1424.
- [23] C. Huiying and L. Youfu, "Optimised particles for 3D trackers", International Journal of Humanoid Robotics, vol. 08, (2011), pp. 749-761.
- [24] W. Zuo and Z. Lin, "A generalized accelerated proximal gradient approach for total variation based image restoration", IEEE transactions on image processing, vol. 10, no. 20, (2011), pp. 2478-2759.
- [25] J. Kwon and K. M. Lee, "Visual Tracking Decomposition", 2010 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), (2010) June 13-18, pp. 1269-1276, San Francisco, USA.
- [26] M. Everingham, L. V. Gool, C. K. I. Williams, J. Winn and A. Zisserman, "The Pascal visual object classes (voc) challenge", International Journal of Computer Vision(IJCV), (2010), pp. 303-338, USA.

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