영상 추적의 Occlusion 문제 해결을 위한 L1 Minimization의 Weighted Parameter 분석

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Weighted Parameter Analysis of L1 Minimization for Occlusion Problem in Visual Tracking

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요 약

최근 들어, 영상 추적(Visual Tracking)에서의 목표물을 sparse coefficient vector로 나타낼 수 있게 되면서, L1 minimization 방법을 이용한 영상처리 속도 향상이 필요하게 되었다. 더 나아가서, L1 minimization 방법은 영상 추적 과정에서 주로 발생하는 occlusion 문제를 해결하는 방법으로 많이 사용되고 있다. 다라서 본 논문에서는 영상 추적 과정에서 발생하는 occlusion 문제의 해결을 위해서 L1 minimization의 parameter를 분석하였다. L1 minimization에는 최소화 결과에 영향을 미치는 weighted parameter가 존재하며, 이들은 고정 상수나 목표물의 중간값, 평균값, 표준편차로 나타내어 진다. 실험 결과를 바탕으로 분석하였을 때, weighted parameter 중에서 평균값이 OPE(One Pass Evaluation)을 기반으로 한 success rate와 precision performance에서 좋은 결과를 갖는 것을 확인할 수 있었다.

ABSTRACT

Recently, the target object can be represented as sparse coefficient vector in visual tracking. Due to this reason, exploitation of the compressibility in the transform domain by using L1 minimization is needed. Further, L1 minimization is proposed to handle the occlusion problem in visual tracking, since tracking failures mostly are caused by occlusion. Furthermore, there is a weighted parameter in L1 minimization that influences the result of this minimization. In this paper, this parameter is analyzed for occlusion problem in visual tracking. Several coefficients that derived from median value of the target object, mean value of the arget object, the standard deviation of the target object are, 0, 0.1, and 0.01 are used as weighted parameter of L1 minimization. Based on the experimental results, the value which is equal to 0.1 is suggested as weighted parameter of L1 minimization, due to achieved the best result of success rate and precision performance parameter. Both of these performance parameters are based on one pass evaluation (OPE).

키워드

weighted parameter, L1 minimization, occlusion, visual tracking, success rate, precision, one pass evaluation

Ⅰ. Introduction

In recent years, visual tracking or object tracking stills be a hot topic in the computer vision area. It is because many applications in the computer vision area need visual tracking such as surveillance [1], human-computer interaction, robotics [2], and etc. Further, the challenging problems also still remain in this research field such as illumination variations, background clutters, scale variations, deformation, motion blur, fast motion, in-plane rotation, out-plane rotation, out-of-view, low resolution, and occlusion. And a factor that mostly made tracking fail is an occlusion.

To solve this problem, researchers propose L1 minimization [3-5] that adapt from compress sensing [6]. Bao et al. [5] proposed accelerated proximal gradient approach in order to make L1 tracker more robust and faster than the previous work [3]. Besides uses L1 minimization, their method also use particle filter to modeling the motion.

Recently, sparse representation is used collaborative model which is consists of discriminative approach and generative approach in visual tracking [7]. And this method uses L1 minimization to represent the target object as sparse coefficient vector [7]. Furthermore, there is a weighted parameter in L1 minimization and this value influence the result in visual tracking.

In this paper, the weighted parameter of L1 minimization is analyzed for occlusion problem in visual tracking. The remainder of this paper is presented in Section 2. In Section 3, Experimental results ar described. Finally, the occlusion is presented in Section 4.

II. Sparse Generative Model

Our tracking is based on sparse generative model [7]. In this method, sparse coefficient vector is used to represent the target object. And this vector can be calculated by

$$\min_{\alpha_i}[\frac{1}{2}\|A_i - D\alpha_i\|_2^2 + \lambda\|\alpha_i\|_1] \quad (1)$$

where A_i, α_i, D, and λ are represent vector from each patch, sparse coefficient vector, dictionary that represent the target object in the first or initial frame, and the weighted parameter, respectively. Then, the sparse coefficient vector is arranged to histogram by

$$\gamma = [\alpha_1, \alpha_2, \cdots, \alpha_N] \quad (2)$$

where γ is the proposed histogram for each candidate region.

Due to handle the appearance variations of the target object, we update the template histogram and the updated template histogram can be calculated as follows

$$\phi_n = \mu\phi_0 + (1-\mu)\phi_f \quad \text{if } SF \le SF_{th} \quad (3)$$

where ϕ_n, ϕ_0, ϕ_f, μ, SF, and SF_{th} are represent new proposed template histogram from first/initial frame, proposed template histogram before update, a weight, similarity value of the result, and similarity threshold, respectively. The weight μ is equal to 0.95 and the SF_{th} is equal to 0.7. Moreover, particle filter is used as motion model in this method.

III. Experimental Results

The image sequence “FaceOcc1” from [8] is used to analyze the weighted parameter λ of L1 minimization. This sequence consists only an occlusion problem and the number of frames in this sequence are 892 frames. We use several values to represent λ such as median value, mean value, standard deviation value, 0, 0.1 and 0.01. Further, the number particle that we used in this research is 50.

Two performance parameters are used in our experiment. These parameters are: success rate and precision; and both are based on one pass evaluation (OPE). A success rate is calculated based on area under curve (AUC) and the threshold. Further, a precision is calculated based on centroid distance between the result and the ground truth and also with the threshold.

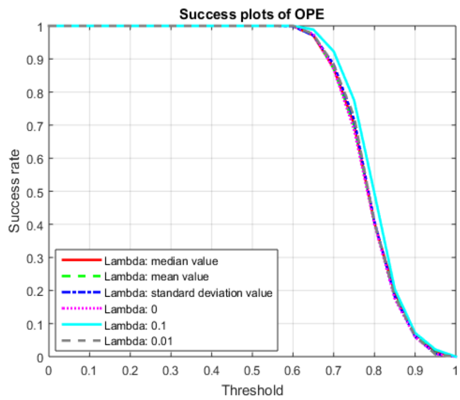

Fig. 1. Success plots of OPE

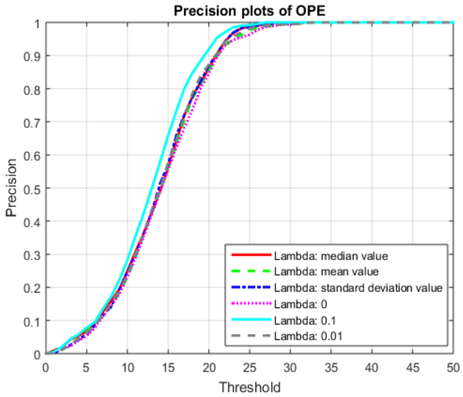

Fig. 2. Precision plots of OPE

The AUC can be calculated by using $AUC = \frac{R_T \cap R_G}{R_T \cup R_G}$, where R_T is the result and R_G is the ground truth. Fig. 1. and Fig. 2. are represent the result of success rate and the precision, respectively.

Based on the results, λ which has value is equal to 0.1 give the best result both of success rate of OPE and the precision of OPE.

Ⅳ. Conclusion

In this research, the weighted parameter of L1 minimization is analyzed for occlusion problem in visual tracking. Based on the experiment with use several values to represent λ such as median value, mean value, standard deviation value, 0, 0.1, 0.01, best result both of success rate of OPE and the precision of OPE are achived by the λ which has value is equal to 0.1.

Several issues still remain about this research such as how to find the optimal value of weighted parameter in L1 minimization for all challenging problem in visual tracking (i. e., illumination variations, background clutters, scale variations, deformation, motion blur, fast motion, in-plane rotation, out plane rotation, out-of-view, low resolution, and occlusion) and etc.

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