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Leaf Recognition Based on Color and Shape Using ADNet

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Abstract
To know the details of plants and leaves around us is of great importance medicinally and economically. Traditionally, plants are categorized by taxonomists through investigation of various parts of the plant. At the same time, most of the plants can be classified and identified based on the leaf shape and associated features. in this paper we USES Image processing techniques to extract leaf color, shape and GLCM features such as mean, standard deviation, homogeneity, correlation, aspect ratio, width ratio, moment ratio, apex angle, apex ratio, base angle, centroid deviation ratio and circularity. This paper proposes an adaptive visual tracking algorithm based on key frame selection and reinforcement learning (RL) Method. At the beginning, the probability value of the RL network output is analysed, and the predicted value of output is normalized. The proposed technic uses only a fine-tuned in key frames to obtain multiple fixed prediction models. The experiment is conducted on 75 video sequences of the Object Tracking Benchmark to verify the effectiveness of key frame selection strategy, and it is Compared with the original reinforcement learning based tracking algorithm.

Keywords: Reinforcement learning, adaptive visual tracking, target appearance, ADNet algorithm, key frame selection.

I. INTRODUCTION

Plants and Leaves have many uses in industry, medicine, and food production. to identify and recognizing plant categories is an important process to obtain necessary raw materials from correct plants. The plant identification and recognition is also important in environmental protection. Moreover, identifying and recognizing plants is a tedious task and is generally done by human expert biologists. To Design an automatic recognition system for plants and leaves is important and useful, so that it can facilitate fast classification of plants, and have applications in many scientific and industrial fields [10]. to identify and discovery of new species like, plant resource surveys, and plant database management are demanding applications in biology, foodstuff, medicine, and agriculture. An Automatic plant and leaves recognition may increase efficiency and speed in fields, save time of human experts, and decrease cost of production stages.

An Automated plant and leaf recognition systems have been carried out by many researchers. Du et al. [10] proposed an automatic plant recognition method, it is Mainly based on digital morphological features of leaf images, which includes geometrical and invariable moment features. It makes uses Move Median Centres (MMC) hyper sphere classifier as the classification method. Wu et al. [22] proposed a leaf recognition algorithm called Probabilistic Neural Networks (PNN). It also focuses on the geometric features: diameter, physiological length, physiological width, leaf area, and leaf perimeter.

Plants are plays vital role in your ecosystem. Plants can be used as foodstuff, in the field of medicines and in many industries for manufacturing various products. Plant identification and classification can be performed using many different techniques. As plants and leaves are common available in our surroundings, it is efficient to identify and classify plants by their leaves. Plant and leaves are classification by using leaves requires different biometric features. Plants are mostly identified and classified by taxonomists and the process is usually lengthy. Plant and leaves features that help in identifying a plant are fruit, seed, flower, root, stem, etc. India is an agriculture country where more than 70% of the population depends on agriculture. Farmers have wide range of diversity to select suitable Fruits, Vegetables and crops. Plants Leaves are used in herbal medicine, soups, stews, meat, seafood and vegetable dishes, etc. So, getting more information of plants growing around us is of great importance medicinally and economically.

Visual tracking is one of the most common research topics in the field of computer vision. With the continuous improvement of computer processing performance and the development of machine learning technology, visual tracking technology has been widely used in military, surveillance, security, intelligent human-computer interaction, intelligent transportation and many other fields. In particular field, a large number of researchers have introduced deep learning into visual tracking. Their aim to improve the performance of the target tracking algorithm by using the excellent feature extraction and target expression ability of deep learning. Ref. [4]. Another research Ref. [5] proposes to acquire the target saliency map by using pre-training convolutional neural network (CNN), and then obtain the tracking result through online support vector machine learning. In Ref. [6], The Multi-layer CNN is used to extract target features, which effectively improves the tracking accuracy and robustness. However, the disadvantage of them using online learning network or support vector machine is that it requires a large number of training samples and operation time.

Along with that, the researchers try to introduce the learning methods such as reinforcement learning and graph model into tracking, to change the traditional tracking algorithm flow. Sangdoo Yun et al. [7] was designs an Action Decision Network (ADNet) based on policy and Y. Ma et al. [8]was pointed out that the visual object is sparse in the feature space. Therefore, an image of the object can be represented by a finite number of other images of the object and an approximate s linear representation of the trivial image set, and its coefficient is sparse. Therefore, WE believed that when the target deforms greatly during the tracking process, the old model cannot match the current target state through online fine-tuning, so a current target model should be retrained in the current state, and a limited number of target models can satisfy the follow-up tracking. Therefore, we introduce an adaptive visual tracking algorithm (KRAT) based on key frame select and reinforcement learning. On base of the ADNet network model, several key frames are selected to obtain the corresponding target model, which is helpful to tracking the target with large deformation and improves the robustness of tracking.

II. The ADNet ALGORITHM

The current tracking algorithms is to extract multiple candidate bounding boxes in each frame and calculate the probability or confidence level of each candidate as the target object, and it takes the candidate with the highest confidence level as the current frame target state. At the same time, the process of ADNet algorithm is different from the above methods. The network can output the movement or scaling behaviour of the target tracking box by network pre-training through reinforcement learning and supervised learning. Now Each action is encoded by an 11-dimensional vector with one-hot form, and the corresponding behaviour of the maximum value in the 11-dimensional vector is selected as the output. At the same time, there is a full-connection layers' parallel to the behaviour output, which outputs a 2-dimensional vector to represent the confidence level of the currently selected behaviour as shown in Figure 1.

In Figure 1, while tracking with the given video sequence, the first step is pre-training the network in the first frame, and next, the candidate target blocks are extracted from the subsequent frames. The best behaviour is obtained after inputting the fine-tuned network, and the candidate target is moved or scaled according to behaviour. Furthermore, the resulting target blocks are taken as input of the fine-tuned network. Such iteration repeats until the network output behaviour is stop or reaches the maximum number of iterations.

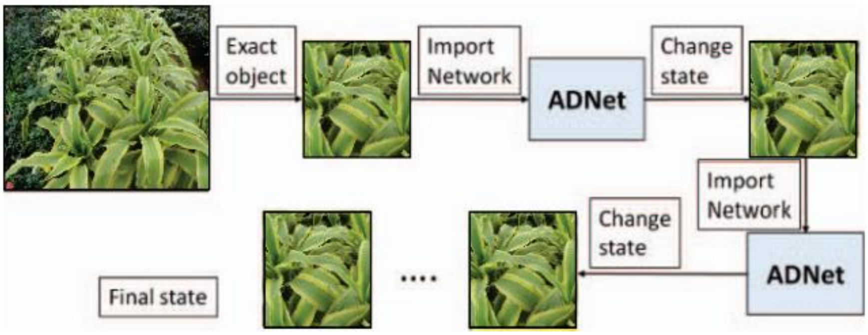

Figure 1. The concept of ADNet tracking

TheADNet tracking algorithm, its direct output of the networkis the 11-dimensional behaviour probability $P_i^{t,m}$ where i=1,2…11 of the mth iteration in frame t and the 2-dimensional predictive confidence $C_j^{t.m}$, j= 1,2…., $P_j^{t,m}$, is thedirect output of the network. For the convenience ofrepresentation and calculation, the algorithm uses normalize the probabilityaccording to its practical significance. The normalizedprobability is denoted by$Q_i^{t,m}$and $Q_i^{t,m}$needs to meet thefollowing requirements.

$$\begin{cases} \sum_{i=1}^{11} q_i^{t,m} = 1 \\ 0 \le q_i^{t,m} \le 1, \forall i \end{cases} \quad (1)$$

Now The normalization method in this paper is expressed by formula (2),

$$\begin{cases} r_i = p_i^{t,m} - \min(p_1^{t,m}, \ldots, p_{11}^{t,m}) \\ q_i^{t,m} = r_i / \sum_{i=1}^{11} r_i \end{cases} \quad (2)$$

where the$R_i$is an intermediate variable and minimization function. the probability value of the correspondent is to the optimal behaviour, which selected for the mthiteration of frame t is $Q_b^{t,m}$= max($Q_1^{t,m}$,…$Q_{11}^{t,m}$,), *b€{1,…11}*.When the tracking quality is high, $Q_b^{t,m}$should besignificantly greater than other values, and from the multipleiterations and continuous frames of each frame, $Q_b^{t,m}$has a certain continuity.

In the new frame, if there is a significant decrease in$Q_b^{t,m}$, andit indicates that the current target has changed greatly, and theADNet model can no longer provide reasonable behaviour prediction.When$Q_b^{t,m}$isnotlarger than the probability mean $E^{t,m}$of other behaviors, where$E^{t,m}=mean\{Q_i^{t,m} |i=1,....11, i\neq b\}$; *and it is smaller than the* maximum probability mean$F^{t,m}$of previous frames, where $F^{t,m}= mean\{ Q_b^{k,m} |t\text{-}10,\ldots ,t\text{-}\}$, then$Q_b^{t,m}$of the current frame.The previous frame of the currentframe is taken as the key frame to learn the new model. That is,the criterion of the proposed key frame selection is $Q_b^{t,m}<\lambda1 \text{ X } E^{t,m}$ *and* $Q_b^{t,m}<\lambda2 \text{ X } F^{t,m.}$ where, λ1 And λ2 are the threshold parameters.

III.THE PROCESS OF KRAT ALGORITHM

Initialization: Import the off-line trained ADNet network and initialize it in the first frame.

for t = 1 to T (T is the total number of frames)

Detection

if t >1 **then**

Step 1: sample image blocks and use multiple key frames separately fine-tuned ADNet network to predict the tracking box behaviour.

Step 2: select the network with the highest prediction confidence for follow-up tracking

End

Training/update

Step 3: calculate theof current

Frame

If $Q_b^{t,m}<\lambda1 \text{ x} E^{t,m}$ ***and*** $Q_b^{t,m}< \lambda2 \text{ x} F^{t,m.}$ **then**

***S*tep 4:** take the previous image as the key frame and sample the positive and negative samples to obtain a new ADNet network model through fine-tuning.

Step 5: store the $Q_b^{t,m}$, $E^{t,m}$, $F^{t,m}$of thecurrent frame and the new model

End

End

IV. EXPERIMENTS

In order to evaluate the performance of the proposed system, a comparative experiment is carried out on the Object Tracking Benchmark (OTB). The OTB 75 contains 75 video sequences, covering the main challenging scenes for visual tracking, such as illumination change, scale variation, occlusion, deformation, motion blur, rapid. The smooth running of proposed system movement, in-plane rotation, out-of-plane rotation, target out-of-view, background interference and low resolution. The smooth conduction of the proposed idea we required a 2.4GHz Intel E5-2630 processor, 64GB of memory and 16 cores.

V. CONCLUSION

In this paper, studies the online updating of the target tracking algorithm model from the perspective of key frame selection. At the beginning, the existing problem of the original ADNet algorithm that the performance of this algorithm decreases when the target is deformed greatly is analysed. Then, according to the sparse representation view, it is believed that the target in a few finite frames can effectively express the target, and a network model with a small amount of fixed online fine-tuning is proposed for tracking. The importance of the key frame selection in the adaptive updating of the model is verified by the comparative experiment of the proposed algorithm, which is of certain guiding significance to the research of the follow up tracking algorithmisof certain guiding significance to the research of the followuptracking algorithm.

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