The Instantaneous Accuracy: a Novel Metric for the Problem of Online Human Behaviour Recognition in Untrimmed Videos

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Abstract

The problem of Online Human Behaviour Recognition in untrimmed videos, aka Online Action Detection (OAD), needs to be revisited. Unlike traditional offline action detection approaches, where the evaluation metrics are clear and well established, in the OAD setting we find few works and no consensus on the evaluation protocols to be used. In this paper we introduce a novel online metric, the Instantaneous Accuracy (IA), that exhibits an online nature, solving most of the limitations of the previous (offline) metrics. We conduct a thorough experimental evaluation on TVSeries dataset, comparing the performance of various baseline methods to the state of the art. Our results confirm the problems of previous evaluation protocols, and suggest that an IA-based protocol is more adequate to the online scenario for human behaviour understanding. Code of the metric available [here](https://github.com/gramuah/ia).

1. Introduction

We focus on recognizing human behaviours in untrimmed videos as soon as they happen, which was coined as Online Action Detection (OAD) by De Geest et al. [4].

The problem of action detection has been widely studied, but mainly from an offline perspective, e.g. [9] [13] [8] [14] [3] [12] [6] [10] [2], where it is assumed that all the video is available to make predictions. Few works address the online setting, e.g. [4] [7] [5]. Think of a robotic platform that must interact with humans in a realistic scenario, recognizing their behaviours. All previous offline methods make this application impossible as they will detect the action situations way later they have occurred. In contrast, OAD approaches must give detections over video streams, hence working with partial observations. However, among the online approaches there is an important weakness in a fundamental aspect: the evaluation metric. We have noticed that there is no consensus on the evaluation protocols, i.e. in each dataset a different metric is proposed for the same problem. Moreover, used metrics cannot be said to be of an online nature. In other words, the proposed metrics for recent online action detection models, such as the mean Average Precision (mAP) or the Calibrated Average Precision (cAP) [4], do not provide information about the instantaneous performance of the solutions over time: they need to be computed entirely offline, accessing the whole set of action annotations for a given test video.

We introduce here an evaluation protocol with a novel online metric: the Instantaneous Accuracy (IA) (see Figure[1]). This metric has been designed not only to overcome the described limitations, but to allow fair comparisons between OAD methods. A thorough experimental evaluation is conducted on the challenging TVSeries dataset [4], offering a comparison between baselines and state-of-the-art.
2. The Instantaneous Accuracy

We argue that an evaluation protocol for OAD must evaluate method performances as the video grows over time with an online video-level metric.

**Previous metrics.** All previous evaluation protocols use class-level metrics which have to be applied offline, i.e. at the end of the test time. These protocols are mainly based on the per-frame mean average precision (mAP) or its calibrated version (cAP) [4].

**Instantaneous Accuracy metric.** Considering a set of $N$ test videos, for each video, an OAD method generates a set of action detections defined by their initial and ending times. IA metric takes as input these detections to build a dense temporal prediction of action (including background) for every time slot $\Delta t$ in the test video. Note $\Delta t$ is the unique parameter of our IA metric and it measures how often the metric is computed. For a particular instant of time $t'$, the $IA(t')$ is computed as the time slot-level accuracy for the action classification task as follows:

$$IA(t') = \frac{\sum_{j=0:\Delta t \cdot T} \bar{t}p(j) + \sum_{j=0:\Delta t \cdot T} \bar{tn}(j)}{K'}$$  

where $\bar{tp}$ and $\bar{tn}$ are two vectors encoding the true positives (actions) and true negatives (background), respectively, and $K'$ represents the total population considered until time $t'$, which is dynamically obtained as follows: $K' = \left\lfloor \frac{K}{\Delta t} \right\rfloor$.

As working with untrimmed videos, where much more background than action frames appear, we propose a weighted version of the IA. Technically, we simply scale in Eq. [1] the true factors by the dynamic ratio between background and action slots until time $t'$ in the ground truth.

To summarise method’s performance across a dataset for research purposes, we propose to use the mean average Instantaneous Accuracy (maIA) for every video:

$$maIA = \frac{1}{N} \sum_{i=1:N} \left( \frac{\Delta t}{T_i} \sum_{j=0:\Delta t \cdot T_i} IA(j) \right)$$  

3. Experiments and conclusions

We use the challenging TVSeries dataset [4], following the setup in [7] to analyse all the metrics considered in our study: mAP, cAP, and the novel online IA.

As baselines, we propose the following: All background (All-BG), which simply simulates a model that never generates an action class; Perfect Model (PM), that always assigns correct labels to action and background frames and helps to reveal the limitations of the previous evaluation protocols, showing their metrics cannot saturate to the maximum which they have been designed for; and finally, we propose a 3D-CNN model, which consists in a C3D network [11] to recognise all actions and the background category.

Table 1 shows the results for these baselines and state-of-the-art model in [4]. First, one observes that offline protocols do not succeed in giving a 100%, even for a perfect method. This is due to their incorrect way of managing the background category. The calibrated AP seems to alleviate this problem, but it still does not achieve a 100%. Second, results from All-BG baseline reveal the relevance of having a weighted metric, especially for an imbalanced problem. And third, 3D-CNN achieves competitive performance when compared to the state of the art, supporting its choice as a strong baseline for the OAD problem. It is only for the cAP where its performance decreases compared with CNN [4], but the reason is that CNN does not cast predictions for background category (while 3D-CNN does), and the cAP has been designed to minimize the importance of such errors.

| Method      | mAP (%) | All-BG | 3D-CNN | PM |
|-------------|---------|--------|--------|----|
| CNN         | 1.9     | 0      | 1.6    | 30.9 |
| cAP         | 60.8    | 0      | 10.8   | 96.9 |
| maIA (%)    | 3.51    | 78.3   | 71.9   | 100 |
| weighted maIA (%) | 12.46  | 22.9   | 28.9   | 100 |

Figure 2a shows the evolution of the weighted IA for a particular video. We use here for visualization 0.5 seconds for $\Delta t$. One can observe how the weighting mechanism works, dynamically adapting the IA to the observed proportion of the video. Figure 2b also shows a comparison between CNN [4] and our 3D-CNN.

As a conclusion, online human behaviour recognition in
untrimmed videos is a challenging task with few contributions. We found limitations in the metrics used so far, so we have introduced a new online metric that complies with the online nature of the problem: the Instantaneous Accuracy (IA). Experimental results have proved both the limitations of previous used metrics and the robustness of IA.

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