An exploration of the performances achievable by combining unsupervised background subtraction algorithms

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Abstract

Background subtraction (BGS) is a common choice for performing motion detection in video. Hundreds of BGS algorithms are released every year, but combining them to detect motion remains largely unexplored. We found that combination strategies allow to capitalize on this massive amount of available BGS algorithms, and offer significant space for performance improvement. In this paper, we explore sets of performances achievable by 6 strategies combining, pixelwise, the outputs of 26 unsupervised BGS algorithms, on the CDnet 2014 dataset, both in the ROC space and in terms of the F1 score. The chosen strategies are representative for a large panel of strategies, including both deterministic and non-deterministic ones, voting and learning. In our experiments, we compare our results with the state-of-the-art combinations IUTIS-5 and CNN-SFC, and report six conclusions, among which the existence of an important gap between the performances of the individual algorithms and the best performances achievable by combining them.

Keywords: motion detection, background subtraction, combination of algorithms, performance, CDnet

1 Introduction

Background subtraction (BGS) aims at detecting pixels belonging to moving objects in video sequences. It has been very popular over the last decade, and has given rise to a massive amount of algorithms predicting either the label BG = 0 (background) or FG = 1 (foreground) in each pixel.

Today, the BGS community is still working hard to find ways to push the performance. An overview of the current status is provided by the changedetection.net platform. It provides the CDnet 2014 dataset with 53 reference videos, grouped in 11 categories, for a total number of 150,000 frames annotated manually at the pixel level. It also makes publicly available the binary outputs of various algorithms. And, last but not least, it helps in comparing algorithms, by reporting performance indicators (such as the error rate ER, the true positive rate TPR, the false positive rate FPR, the F1 score, etc.), and offers an up-to-date ranking.

Currently, the effort is almost exclusively focussing on the development of new algorithms, with hundreds of them being designed every year. Their principles can be found in the surveys [2, 3, 4, 5]. Despite the importance of the effort put in this path, the performance reported on CDnet is saturating.

An alternative path consists in combining algorithms [6]. Surprisingly, only a few papers took this path. The current state-of-the-art combinations are IUTIS-5 [7] and CNN-SFC [8], which have been obtained by learning.

In this paper, we are also considering the combination of BGS algorithms. Our contributions are the following.

First, we innovate by expressing the set of all performances achievable by combination, rather than discussing a unique algorithm. More precisely, we explore the pixelwise combinations of 26 unsupervised BGS algorithms, with 6 combination strategies. We also innovate by deliberately focussing on the combination of the outputs, instead of the intrinsic mechanisms for dealing with the input pixel values.

Second, we point out that the CDnet 2014 platform remains largely underexploited, and show that the availability of BGS algorithm segmentation masks makes it possible to go beyond the produc-
2 Exploration methodology

Our exploration methodology is built upon the following terms, further discussed in the subsections: (1) what we combine, (2) how the combinations are performed, and (3) how the performance is measured.

2.1 The combined algorithms

We have chosen a set of BGS algorithms for which the binary segmentation masks (outputs) are publicly available on the CDnet platform. They are listed in Table 1 with their relative ranks in the leaderboard. Despite that some of these 26 unsupervised algorithms use random numbers, we consider them as deterministic as only one output is uploaded on the platform. We run experiments in which the 26 algorithms are combined, and others in which number of combined algorithms is limited to 9, which is more realistic in practice.

2.2 The combination strategies

We have chosen the following strategies to combine the outputs of the chosen algorithms at the pixel level.

**All Combinations.** In a stochastic perspective, the behavior of any combiner is given by the probabilities of predicting FG for each of the $2^n$ possible joint outputs for the $n$ combined algorithms. Thus, any combiner can be seen as a point of the $[0,1]^{2^n}$ hypercube, and the $2^n$ deterministic combiners $\{0,1\}^n \rightarrow \{0,1\}$ can be seen as its vertices $\{0,1\}^{2^n}$.

**Random Choice.** A subset of combinations can be obtained by choosing, at random and according to fixed probabilities, either BG, FG, or one of the combined outputs.

**Deterministic combinations.** Some deterministic combinations can be obtained by thresholding “soft combinations” whose output is a confidence. Examples include the proportion of algorithms predicting FG $\overline{\text{Prop. FG}}$, the Averaged Bayes classifier $\overline{\text{BKS}}$, and BKS $\text{BKS}$. To the best of our knowledge, BKS has never been applied to BGS algorithms. The Majority Vote, defined for any odd $n$, is a particular case of $\overline{\text{Prop. FG}}$ with the threshold value $\tau = 1/2$. Note that there is no guarantee to improve the performance by the majority vote $\overline{\text{BKS}}$. The formulas for these four strategies are given in Table 2 with the respective number of distinct combinations that can be obtained by tuning $\tau$.

Implementing Averaged Bayes requires the knowledge of the precision and false omission rate of all combined algorithms. For BKS, we need to know the probability of foreground for all the possible joint outputs of the combined algorithms. These quantities are estimated empirically from a learning set. In order for our results to be comparable with IUTIS-5 and CNN-SFC, we used the same learning set $LS$ as in those papers. It is obtained by aggregating all pixels from the shortest video in each category of CDnet. This learning set has more than a billion training samples, which is enough to estimate the quantities needed by Averaged Bayes and BKS.

| Rank | Algorithm | Rank | Algorithm | Rank | Algorithm |
|------|-----------|------|-----------|------|-----------|
| 7    | CWisarDRP | 14   | Averaged  | 20   | Euclidean |
| 3    | CWisarDH  | 12   | FTSG      | 23   | KDE       |
| 4    | CWisarDH  | 15   | Multiscale| 22   | EFIC      |
| 2    | SC_SOBS   | 16   | MBSv0     | 25   | SharedModel |
| 1    | PAWCS     | 32   | MBSv0     | 26   | SuBSENSE  |
| 8    | BMoG      | 21   | SuBSENSE  | 27   | FTSG      |
| 5    | BMoG      | 24   | SuBSENSE  | 28   | KDE       |
| 6    | BMoG      | 29   | SuBSENSE  | 29   | KDE       |
| 10   | SuBSENSE  | 30   | SuBSENSE  | 30   | KDE       |
| 9    | SuBSENSE  | 31   | SuBSENSE  | 31   | KDE       |

Tab. 1: Set of unsupervised BGS algorithms to be combined.
In the ROC space, the set of performances achievable by choosing one algorithm at random corresponds to the convex hull of the individual performances. In particular, for $n = 2$, it corresponds to the line segment between the individual performances. Note that a similar property is known in the classical (unweighted) ROC space [77].

3 Implementation overview

3.1 With the strategy Random Choice

In the ROC space, the set of performances achievable by choosing one algorithm at random corresponds to the convex hull of the individual performances. In particular, for $n = 2$, it corresponds to the line segment between the individual performances. Note that a similar property is known in the classical (unweighted) ROC space [77].

3.2 With the strategy All Combinations

Any given combination can be expressed as a random choice between some $(2^n + 1)$ deterministic combinations. Thus, the set of all performances achievable by combining the outputs of $n$ algorithms is, in ROC, the convex hull of the performances achievable with the $2^n$ deterministic combinations. When $n$ is large, measuring the performances of all the $2^n$ deterministic combinations is unrealistic ($2^n = 1.0938 \times 10^{20201781}$ with $n = 26$). But, as $TPR$ and $FPR$ are linear with respect to the probabilities to predict FG for the $2^n$ possible joint outputs, the achievable area in ROC is a linear projection of the hypercube $[0,1]^{2^n}$, that is a zonotope. We discovered an efficient way to compute the vertices on its contour, making it possible to compute the set of achievable performances for large values of $n$ (even for $n = 26$). For selections involving fewer BGS algorithms, we obtain an achievable zonotope per selection and compute the contour of the union of all these zonotopes.

3.3 With the other strategies

With the other strategies, we proceed by testing each combination exhaustively, with an optimized software. Note that there are 5 millions possible selections of $n \leq 9$ algorithms out of 26. Just to illustrate how difficult it has been to explore their combinations, the number of possible combinations is $5.6585 \times 10^9$ for the Majority Vote, $4.7002 \times 10^7$ for Prop. FG, and $2.0954 \times 10^9$ for Averaged Bayes and BKS. In addition, each combination requires to read 12 billions pixels.

4 Results and observations

We analyze the sets of achievable performances for the 6 combination strategies and 26 unsupervised BGS algorithms.

A huge potential for the pixelwise combinations. Figure [1] shows individual performances and sets of achievable performances in ROC. According to it, the margin for improving the BGS performance is huge. Some pixelwise combinations of outputs (All Combinations) can drastically outperform all the individual BGS algorithms listed in Table [1]. They
Fig. 1: The ROC space with the 26 BGS algorithms (●), previous state-of-the-art combination results (● for IUTIS-5 [7] and ● for CNN-SFC [8]), and the sets of achievable performances with the strategies Random Choice (□ for n = 26, see Section 3.1) and All Combinations (□ ∪ ■ for n ≤ 9, and □ ∪ ■ ∪ ■ for n = 26, see Section 3.2).

It is worth investigating combinations of BGS algorithms. Figure 3 shows that the best $F_1$ scores are, for $n > 1$, significantly better than those obtained without combination ($n = 1$). This suggests that looking for efficient combinations of existing BGS algorithms or developing new BGS algorithms complementary to the existing ones, even if not necessarily better, might be more profitable than searching for the best algorithm. Despite the fact that this conclusion was already drawn in [6], the BGS community continues to propose hundreds of new BGS algorithms every year, the best of which work barely better than the state of the art, without investigating the contribution of the proposed algorithms when combined with those already described in the literature.

How should we combine? Figure 3 also helps in observing that our four deterministic strategies achieve the same maximal $F_1$ score for $n \in \{2, 3\}$. For $4 \leq n \leq 9$, the ranking according to $F_1$ is: $\text{Majority Vote} \leq \text{Prop. FG} \simeq \text{Averaged Bayes} \leq \text{BKS}$. Despite that, the improvement of Averaged Bayes and BKS performance is too small to balance their much larger amount of combinations to test in practice.
5 Conclusion

What should we combine? For any given \( n \), it might be tempting to combine the top-\( n \) algorithms. In fact, Figure 3 shows that we can do much better by carefully cherry picking the combined BGS algorithms among all the available ones (see colored bars vs. gray bars). Moreover, the difference in performance between a colored bar and the corresponding gray bar is, in most cases, greater than the difference in performance between adjacent gray bars. This suggests that knowing precisely what to combine is more important than knowing precisely how to combine. Poorly ranked algorithms can be useful when combined with others, even if they do not perform well alone. This is illustrated in Table 3, where we can observe that our best result are obtained by selecting algorithms in different zones of the leaderboard.

A new “state-of-the-art” \( F_1 \) score on CDnet 2014. Our four deterministic strategies can outperform IUTIS-5 and CNN-SFC when the combined algorithms and the threshold \( \tau \) are adequately chosen. As shown in Table 3, our results establish a new “state-of-the-art” \( F_1 \) score of 0.8487 on CDnet 2014, against 0.8243 for the previous one.

5 Conclusion

To push the performance in BGS, one can either develop new algorithms and publish their results on CDnet, or develop combinations based on the results already available on this platform. Our results show that such combinations have the potential to outperform the individual algorithms. This has resulted in six conclusions. Our findings were all made possible thanks to the availability of outputs on the CDnet platform, a choice that should be promoted for all challenges!

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