Imbalanced Learning for Robust Moving Object Classification in Video Surveillance Applications

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Abstract In the context of video surveillance applications in outdoor scenes, the moving object classification still remains an active area of research, due to the complexity and the diversity of the real-world constraints. In this context, the class imbalance object distribution is an important factor that can hinder the classification performance and particularly regarding the minority classes. In this paper, our main contribution is to enhance the classification of the moving objects when learning from imbalanced data. Thus, we propose an adequate learning framework for moving object classification fitting imbalanced scenarios. Three series of experiments which were led on a challenging dataset have proved that the proposed algorithm improved efficiently the classification of moving object in the presence of asymmetric class distribution. The reported enhancement regarding the minority class reaches 116% in terms of F-score when compared with standard learning algorithms.

1 Introduction

According to the increase in the rate of delinquency, criminality and terrorism acts over the last decade, the intelligent video surveillance systems are essentially focused on the automatic detection of abnormal events. The performance of the observed-events analysis step is closely dependent on the quality of the low level-treatments which consists in the detection, tracking, and classification of moving objects. The latter has continued to prosper and evolve owing to its potential application in a variety of fields such as event understanding [1], human action recognition [2] and smart video surveillance systems [3]. Our research framework is integrated in this context to propose and develop solutions for moving objects classification. In fact, the classification consists in identifying the class of the detected object. According to the literature studies, two main categories can be distinguished: handcrafted feature-

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based methods and deep learned feature-based methods. The former category of methods follows two main steps. At first, a feature set is extracted to describe and represent each detected moving object. The features can be related either on shape (area, silhouette, edges, Histogram of Oriented Gradients, etc.), texture descriptors (Markov Random Field, Local Binary Pattern, etc.), and/or movement such as speed, direction and periodicity of the tracked objects [4]. Thereafter, the feature vector is fed to a particular classifier in order to identify the class of each object. In the literature, several classifiers have been used and combined in order to achieve the best classification accuracy, including K-Nearest Neighbor (KNN) [5], Support Vector Machine (SVM) [6], Multi-Layer Perceptron (MLP) [7]. Regarding the deep learned feature-based methods, authors classify the detected moving objects based on convolutional neural network set either to new CNN architectures [8] or to pre-trained ones [9] so as to resolve their classification task.

Although the investigations on moving object classification were considerably developed in the literature, it still remains an active research area particularly in outdoor scenes, due to the complexity and the diversity of real-world constraints as well as the data characteristics like the presence of noisy, overlapped, and imbalanced data. Indeed, when the handled task is not linear, which is the case in several real-life applications, the class imbalance can hinder the classification performance towards the majority class. However, the rare class may have the highest error cost. This problem is omnipresent in many applications such as the activity recognition [10], the behavior analysis [11],etc. Specifically, our study handles the video sequences so as to detect groups of persons which can cover abnormal activities such as fighting, robbery, burglary, etc. Hence, three main classes are taken into account: $Pedestrian$, $Vehicle$ and $Pedestrian\ Group$. To highlight the class imbalance problem in our study context, we have conducted an estimation of each class presence in three of the most well-known video sequences used for video surveillance applications in an outdoor scene [12, 13, 14]. In fact, all the foreground regions were extracted in order to estimate the presence of each class in the considered sequences. In Table 1, we presented the recorded estimation of the class distributions in a few sequences. An imbalanced class distribution is evident over the different sequences. In general, when learning from imbalanced data, the minority class is misclassified towards the majority classes due to the internal bias of the standard learning algorithms, which consider even misclassification errors on all classes and just look for maximizing the overall accuracy. In our context, the presence of *Pedestrian Group* may refer to dangerous events, which let their misclassification hide several crimes. Hence, it is important to give more focus on the prediction of this class so as to prevent the violence scenarios.

In the imbalanced learning context, literature solutions were proposed mainly on data and algorithm levels. Regarding the first strategy, authors balance data by either over-sampling or under-sampling techniques [15]. Whereas, in the second strategy, data is maintained and only algorithms are modified internally so as to take into account the class imbalance [16, 17]. In order to enhance the prediction performance when handling video sequences presenting a class imbalance, the literature studies focus either on the complexity of the outdoor scene conditions (*e.g.,* the inter-object

Table 1 Class Imbalance Distribution in Video Surveillance Scenarios

Data sets	Pedestrian	Pedestrian Group	Vehicle
OTVBVS [12]	88.98%	11.02%	0%
Groupe Fight (GF) [13]	26.98%	13.35%	59.67%
Visitor Parking (VP) [13]	17.09%	0%	82.91%
Parking Snow (PS) [13]	93.8%	2.2%	4%
Baseline [14]	46.78%	2.29%	50.93%
Intermittent Object Motion [14]	60.07%	1.53%	38.4%
Shadow [14]	59.33%	21.38%	19.29%

similarity) or on the class imbalance regardless the particularities of the application context, but rarely on both directions. In [19], for example, authors have opted for over-sampling strategies to balance their dataset so as to add synthesized frames representing rare objects. Their findings show poor performances regarding the minority classes which drop until 0.323 in F-score. L. Zhang *et al.* have proposed in [18] a class imbalance loss function to support the recognition of rare objects. Although their approach allowed a slight improvement (*i.e.,* 2%), it is still insufficient. In another recent study [20], authors proposed Rk-means++ to improve the localization accuracy of the objects to be recognized and used Focal Loss introduced in YOLOv2 [21] to decrease the imbalance between the positives and negatives. The obtained results show an improvement in the recognition of the different classes regarding the state-of-the-art works, but this improvement does not exceed 6% when focusing on the minority class. Such statements show that handling the class imbalance in video surveillance system is a challenging problem and need to be more investigated.

To improve the prediction of the rare moving objects (*i.e.,* the Pedestrian group) in a multi-class classification problem, an algorithmic solution based on an Asymmetric Entropy for Classifying Imbalanced Data (AECID) and a Random Forest (RF) ensemble learning was proposed in this paper. Originally, AECID was introduced on our previous work [22] to build asymmetric decision trees able to weight the class probabilities in favor of the minority classes. RF from another side proves its efficiency in different application domains since the randomness in the baseline decision trees improves the efficiency and the robustness of the single learners. Therefore, our proposal, referred as RF-AECID, focuses on taking advantage of AECID decision trees in a RF algorithm to enhance the prediction of the rare moving objects in the video surveillance sequences. Although Deep Neural Networks DNN are largely used on computer vision, deep learning from class imbalanced data set is understudied and statistical comparison with the newest studies across a variety of data sets and imbalance levels does not exist [23]. Hence, in the present work, we carried out a comparative study to rank our approach with DNN based strategies rather than traditional learners. The rest of this manuscript is organized as follows: Section 2 describes our approach to improve the moving object classification, Section 3 evaluates the efficiency of our proposed process on different situations, and Section 4 concludes and draws further investigations.

2 Methodology

Our method aims to generate a prediction model for classifying moving regions into one of the three classes *Vehicle*, *Pedestrian*, and *Pedestrian Group*. Hence, our process relies on three steps: the data collection, the feature extraction and the model generation as shown in Figure 1. The details of each step are depicted on the following subsections.

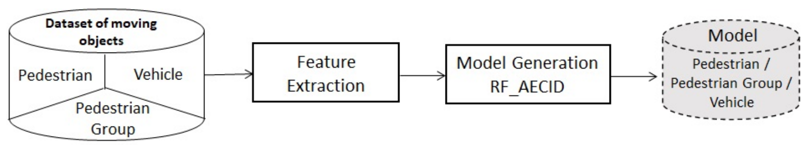

Fig. 1 Proposed approach for imbalanced learning for moving object classification

2.1 Data collection

The collection of a rich and representative learning dataset is a critical step in each machine learning process. To validate our approach, we relied on three well-known video sequences used in the context of video surveillance applications such as the *OTCBVS* [12], the *INO Video Analytics* [13] and the *CD.net 2014* [14] datasets.The introduction of the selected sequences results in a learning dataset sized of 19806 objects described by 151 handcrafted features or 1000 learned features extracted through deep learning strategies. The whole dataset shows a moving objects class imbalance across the three classes *Pedestrian*, *Vehicle*, and *Pedestrian group* classes according the following proportions 61.76%, 30.86%, and 7.38% of the whole dataset, respectively.

2.2 Feature extraction

The feature extraction step aims to provide a representation of each moving object by a feature vector. In our present study, we explored two feature extraction strategies so as to produce either handcrafted features or deep features generated through deep learning models. The investigation on both methods allows the comparison of their performance firstly and the capture of their impact on the training model performance, secondly. On the one hand When dealing with handcrafted features, we have opted for a feature set based on shape and movement [26]. On the other hand, being encouraged by the great surge and the high performance of convolutional neural network (CNN), we investigated our model generation method on deep features generated by a pre-trained deep CNN model. In the state-of-the-art studies, there is a wide range of CNN models trained on huge datasets for several data mining applications. Darknet-53 ranks among the most well-known convolutional neural networks. It was used as a feature extractor to classify detected objects in the YOLOv3 [27] and it achieved a high classification performance on the ImageNet dataset. Thus, adopting DarkNet-53 CNN model to generate deep features seems to be a promoting strategy.

2.3 Model generation

To handle the class imbalance, we proposed an algorithmic solution prone to enhance the classification of moving objects when faced with multi-class imbalanced data. Our proposal, referred as RF-AECID, handles the class imbalance by using asymmetric baseline decision trees. In fact, they rely on an off-centered entropy, named AECID. It is an impurity measure serving on splitting the tree nodes of each level into the least impure partition. Contrary to the common symmetric split criteria, AECID weights inequitably the probability of belonging to each class according to the prior class distribution supposed to be imbalanced. For binary classification, AECID entropy was originally defined on our previous work [22]. The asymmetric property is due to the imbalanced weights associated to each class according to the asymmetric prior class distribution, which let such measure fit each problem's characteristics. The effectiveness of AECID decision trees comes also with the dynamic tuning of the AECID's parameters so as to fit the considered classification task. We refer any interested reader to our previous studies [22] and [29] for more details proving the robustness and the effectiveness of AECID-DT in several application fields. In the perspective of boosting the learner performance, we introduce the asymmetric decision trees as a baseline classifier into an ensemble learning framework, particularly the Random Forest (RF) [30]. It is a bagging classifier based on random trees which aggregates the prediction of multiple accurate and diverse binary classifiers. Based on several studies including [31] and [32], RF is proved to improve the diversity of the baseline classifiers thanks to the randomness of the bootstrapped training sets along with the randomness of the feature selection. To train the learning model from the multi-class dataset, we opt for the Error-Correcting Output Codes (ECOC) technique to re-frame the multi-class classification problem as multiple binary classification problems, allowing thereby the direct use of native learners. The ECOC approach is known to be simple yet powerful approach to deal with a multi-class problem [28].

3 Experimental Results

In order to evaluate the performance of our moving object classifier learned from imbalanced data (*i.e.,* RF-AECID), we carried out a comparative study of our approach regarding well-known literature classifiers, namely Decision Trees (DT), Random

Forest (RF), Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), Logistic Regression (LR), along with different Convolutional Neural Network (CNN) based strategies. Hence, we conducted three experimental series. In the first and the second series, the classification performance is reported regarding standard learners following however different strategies of feature extraction. In fact, it was handcrafted in the first series, whereas automatically labored by a deep CNN model (*i.e.,* DarkNet-53) in the second series. In the third series of experiments, we compare RF-AECID based on deep learned features with different deep CNN models ranking among the most well-known ones. Therefore, our comparative study includes both standard and recent well-known approaches which were already implemented, thereby making their evaluation possible on our dataset. To perform our approach, we relied on the scikit-learn API [33] after having implementing our AECID asymmetric entropy [22]. The ECOC binarization technique as well as the competitive learners including DT, RF, SVM, GNB, and LR were based on the default setting of the latest API. To evaluate the competitive approaches, we relied on Precision and Recall so as to capture the performance on each class separately, F-score as a harmonic mean joining Precision and Recall, and Accuracy as an overall evaluation measure. We carried out our experiments using 5 stratified cross validation. Therefore, the reported values in Tables 2, 3, and 4 were achieved by averaging the results of the 5 folds regarding the considered evaluation measures. The moving objects classified, respectively, as *Pedestrian*, *Pedestrian Group* and *Vehicle* will be assigned to the following labels 0, 1 and 2 in the comparison result tables.

3.1 Evaluation of RF-AECID based on handcrafted features

We present in Table 2 the comparative results of RF-AECID with the aforementioned learning algorithms. The presented results highlight the classification performance on the different classes, in which Class 1 refers to the minority class. At first glance, it is shown that RF-AECID performed the best in terms of Accuracy. In overall, RF-AECID enhances in general the precision, recall and F-score regarding all classes. This enhancement varies from a class to another. In fact, in terms of precision, it reaches 6.9% and 7% for Class 0 and Class 2, respectively. For the minority class, RF-AECID proved also a significant improvement of precision which reaches 60%. According to the recall rates, RF-AECID, LR, and SVM show the best results with slight differences. Since, a tradeoff is obvious between precision and recall, we rely on F-score which proves the effectiveness of RF-AECID almost for all classes.

3.2 Evaluation of RF-AECID based on deep learned features

Encouraged by the success of convolutional neural network (CNN), we evaluate our model generation algorithm on deep features generated by the DarkNet-53 CNN

Table 2 Comparative classification results based on handcrafted features

	Precision			Recall			F-score			Accuracy
	0	1	2	0	1	2	0	1	2	
DT	0.922	0.483	0.903	0.902	0.422	0.842	0.911	0.378	0.819	0.883
RF	0.932	0.751	**0.973**	**0.985**	0.404	**0.983**	0.957	0.475	**0.978**	0.944
RF_AECID	**0.942**	**0.811**	0.972	0.979	0.513	0.977	**0.96**	**0.567**	0.974	**0.945**
SVM	0.939	0.576	0.954	0.939	0.541	0.968	0.939	0.522	0.96	0.933
GNB	0.877	0.324	0.935	0.89	0.223	0.852	0.869	0.124	0.842	0.906
LR	0.94	0.592	0.952	0.941	**0.545**	0.966	0.94	0.546	0.959	0.934

model. Table 3 displays the comparison results of our method and the learning algorithms (*i.e.,* DT, RF, SVM, GNB and LR). The reported results show comparable performances across learning algorithms. However, the performance of RF-AECID is clearly enhanced in particular regarding the minority class. In fact, F-score on Class 1 goes from 0.567 to 0.704. Such statement shows, once again, the efficiency of RF-AECID even when it is coupled with deep learned features.

Table 3 Comparative classification results based on deep learned features

	Precision			Recall			F-score			Accuracy
	0	1	2	0	1	2	0	1	2	
DT	0.816	0.476	0.684	0.918	0.376	0.67	0.862	0.4	0.676	0.802
RF	0.918	0.746	0.782	**0.98**	0.54	0.748	0.95	0.53	0.764	0.876
RF_AECID	0.933	**0.867**	0.967	0.975	0.625	0.946	**0.953**	**0.704**	0.956	**0.940**
SVM	**0.956**	0.624	**0.974**	0.938	0.762	**0.95**	0.946	0.668	**0.96**	0.928
GNB	0.866	0.318	0.664	0.774	0.52	0.668	0.81	0.326	0.668	0.724
LR	**0.956**	0.642	0.77	0.954	**0.78**	0.782	0.952	0.662	0.776	0.889

3.3 Evaluation of RF-AECID versus CNN architectures

The main purpose of this series of experiments was to validate the robustness of the proposed method for moving object classification compared to the use of pre-trained deep CNN. In fact, we have confronted our classification results, relied on deep features, with those obtained by well-known deep CNN models dedicated to the classification task in computer vision field (DarkNet-53 [27], ResNet-50 [34], AlexNet [35] and VGG-19 [36]). Table 4 reports the obtained results. In terms of F-score, our method records the best rates in all moving object classes. As for recall and precision, we have achieved the best results in the minority class (Class 1) compared to those of deep CNN model. In fact, the F-score enhancement reaches 337% (when compared with VGG19 architecture). It is worth noting that when being based also on the same deep feature extraction strategy (DarkNet53), the observed gains are still significant and reaching more than 159% of F-score enhancement. These results confirm that the deep learning-based methods still providing limited performances when dealing with imbalanced data.

Table 4 Comparison of the performance of the proposed method with well-known deep CNN models

	Precision			Recall			F-score			Accuracy
	0	1	2	0	1	2	0	1	2	
DarkNet53	0.829	0.374	0.879	0.872	0.208	**0.966**	0.85	0.268	0.92	0.814
ResNet50	0.841	0.163	0.965	0.869	0.248	0.862	0.855	0.197	0.911	0.837
AlexNet	0.781	0.289	0.848	0.832	0.239	0.806	0.806	0.262	0.826	0.769
VGG19	0.777	0.186	0.851	0.844	0.14	0.805	0.809	0.16	0.827	0.761
RF_AECID	**0.933**	**0.867**	**0.967**	**0.975**	**0.625**	0.946	**0.953**	**0.704**	**0.956**	**0.940**

4 Conclusion

In this paper, we propose a complete framework for moving object classification which takes into account firstly the challenges of the outdoor scene sequences and secondly the challenge of the class imbalance. Hence, the first contribution concerns the prior model learning step which prepares the learning data. In this context, two strategies were investigated for the feature extraction step: 1) deep-learned feature extraction, and 2) handcrafted feature extraction based on combining shape-based features with velocity so as to overcome the inter-similarity objects. Our second contribution concerns handling imbalanced data during the model training step based on asymmetric decision trees using an asymmetric entropy AECID as a node split criterion. The entire approach was compared, in a first time, with some well recognized learning algorithms (DT, RF, GNB, SVM, and LR) and four well-known deep CNN architectures (DarkNet-53, ResNet-50, AlexNet, and VGG-19), in second time. The reported results show at first the efficiency of our approach regarding the competitive classifiers on enhancing the classification performance of moving objects in overall and particularly regarding the minority class. A second remark states that the handcrafted and the deep learned feature extraction provide competitive results, unless a better prediction regarding the minority class was mainly proved by the second strategy when RF-AECID is considered. The third comparative study considering the CNN models and RF-AECID joined with deep-learned feature extraction have proved spectacular gains on the minority class in favor of our approach. Our findings open several horizons for future works. A first axe can investigate more sophisticated learning algorithms underlining for example better tuned ensemble frameworks regarding the class imbalance problem. A second research field can also interest the enhancing of the ECOC framework allowing the transition from the multiclass to the binary classification in such a way to better fit imbalanced data. Further investigations of other class imbalance approaches like sampling strategies joined with ensemble learning frameworks rank as well among our first interests.

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