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# An Approach to the Feature Selection in the Objects Detection Problem in Images

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**Abstract.** The objects detection problem in images has been considered. It is known that this problem can be solved using the SVM classifier development with application of the descriptors of the histograms of oriented gradients for creation of the training and test sets, but this technics deals with the significant time expenses for the formation of the histograms and the development of the SVM classifier. The application of the special tool known as the feature selection using the neighborhood component analysis algorithm for classification to determine the most informative features of objects has been investigated. It is shown that this approach allow to reduce the time expenses on solving the objects detection problem while maintaining acceptable values of the classification quality indicators. The experimental results on solving the objects detection problem have been presented.

## 1. Introduction

The information technologies development has led to the emergence of the digital types of information, which made it possible to obtain the data using the automated systems. To realize this possibility, a large number of various algorithms, which allow analyzing the video data, can be used. The video data analysis is associated with the concept of the “video analytics”. Video analytics is a technology that uses the computer vision techniques to solve various video data analysis problems.

The objects detection problem using the images or video data is one of the important problems of the computer vision. The purpose of detection is to determine whether there is a desired object on the incoming image.

Algorithms that solve this problem are used in the development of the modern interfaces for the interaction of systems and humans. Such algorithms are, for example, used in the robotics, in the tracking systems, in the security systems, etc. The problem of detection is reduced to finding the objects of a predetermined class in the image. In this case, when selecting objects in the image, the desired objects can be considered as the sets of pixels corresponding to them, or as the conditional rectangles bordering these objects. In this paper, the selection of the desired objects in the rectangles will be used, and as a toolkit for the classification of selected objects, the SVM classifier based on the SVM algorithm will be used [1 – 3]. Also, the HOG descriptor (Histogram of oriented gradients) realizing the counting of the number of gradient directions in local areas of the image will be used.

HOG descriptor allows to get a feature vector that describes the shape of objects in the image. This feature vector can be used for training in the development of various classifiers using the appropriate algorithms. The authors of the HOG descriptor proposed the use of a linear SVM classifier. A



herewith the indicate the following disadvantages of this approach to the development of the SVM classifier [4]: the presence of the significant time expenses for both the formation of the histograms and the development of the SVM classifier based on the dataset received with calculating of these histograms.

The purpose of this work is the study of the dependency of the results of the SVM classifier development using the dataset formed on the basis of the HOG descriptor, from the number of the considered features of objects in this dataset. As part of this study, it is proposed to use the special tool known as the feature selection to determine the most informative features of objects of the training set, that should allow to reduce the time expenses on solving the objects detection problem while maintaining acceptable values of the classification quality indicators.

## 2. Decision of the objects detection problem

The decision of the object detection problem can be divided into the following steps.

1. The generation of features: the choice of those features that describe the object with sufficient completeness (within reasonable limits).
2. The feature selection: the selection of the most informative features for classification.
3. The classifier development: the choice of the decision rule according to which, based on the feature vector, the object is assigned to the particular class.
4. The assessment of the classification quality.

The descriptors solve the problem of the image description. The descriptor provides a description of the singular point, which determines the features of its neighborhood, and represents a numerical or binary vector of the certain parameters. The descriptor allows selecting the singular point from the set of all points in the image.

We used the HOG descriptor to describe the features of objects. HOG is a feature descriptor used to detect the objects in computer vision and image processing. The HOG descriptor technique counts occurrences of gradient orientation in localized portions of an image – detection window, or region of interest [4].

The main problem of application of the HOG descriptors is the huge number of the generated features that lead to the significant time expenses on the classifier development (in the context of the object detection problem). Therefore, it is necessary to make the feature selection.

We suggested to make the feature selection using the neighborhood component analysis (NSA) algorithm for classification [5 – 7]. This algorithm performs the feature selection for classification using the predictors (the inputs of the dataset) and the responses (the output of the dataset). It finds the feature weights by using a diagonal adaptation of the NCA with regularization. The weights of the irrelevant features will be close to zero.

This algorithm finds the neighborhood component analysis model for classification using Stochastic Gradient Descent (SGD). SGD is a simple yet very efficient approach to discriminative learning of linear classifiers under convex loss functions.

In the context of solving the problem of the objects detection, it will be necessary to define the classification rule, that is, the rule for assigning the object to the particular class. In the case of the binary classification, two classes are considered: “object is detected” and “object is not detected”.

One of the algorithms that successfully solve this problem is the SVM algorithm used to develop the SVM classifier.

The main feature of the SVM classifier is the use of the kernel function which is applied to transfer the experimental dataset from the original feature space to a higher dimension space, in which the hyperplane separates the classes is built. Moreover, on both sides of the separating hyperplane, two parallel hyperplanes, defining the boundaries of the classes and located at the maximum possible distance from each other, are built.

As a result of the SVM classifier training, the separating hyperplane, which can be given by the following equation is defined [1 – 3]:

$$\langle w, z \rangle + b = 0,$$

где  $w$  is the perpendicular vector to the separating hyperplane;  $b$  is the bias,  $z$  is the object.

A herewith, the support vectors that are closest to the hyperplane separating the classes and carry all the information about the classes separation are determined.

The classification decision that associates the object  $z$  with the class marked by “-1” or “+1” is made in accordance with the rule [1 – 3]:

$$F(z) = \text{sign}(\langle w, z \rangle + b).$$

To assess the classification quality, usually the following indicators are used: overall accuracy, sensitivity, specificity, F-measure, the errors of the 1-st and 2-nd types. Also, it is useful to assess the number of the support vectors for SVM classifier.

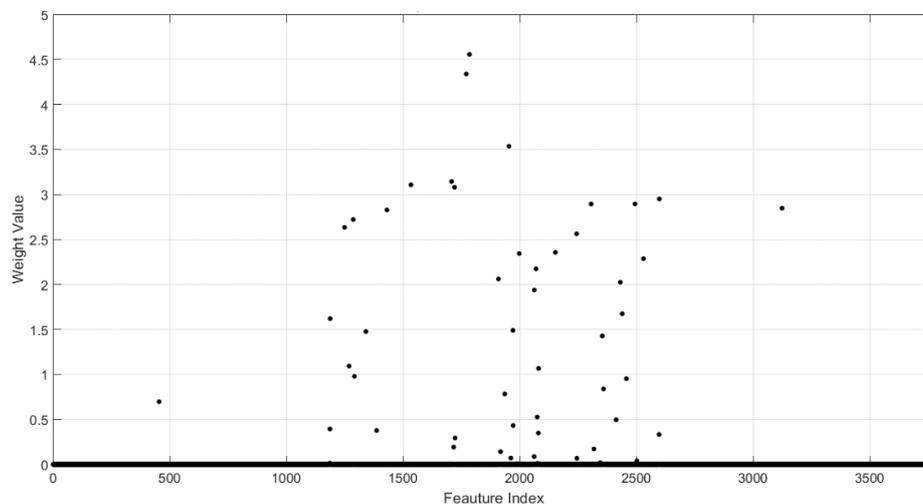
### 3. Experimental studies

The experimental studies were performed with the INRIA Person Dataset. The characteristics of this dataset are shown in table 1.

To assess the quality of the obtained SVM classifiers, the hold-out validation method was used. A herewith, the proportion of the test set in the experimental dataset was equal to 0.2.

In these experiments, the parameters of the SVM classifier were taken by default equal to the following values: the value of the regularization parameter  $C = 1$ ; the value  $\sigma = 1$  for the radial basis kernel function.

The experiments were conducted using a PC with Windows 10 operating system, based on the Intel Core i3-4160 processor with 8 GB RAM. The MATLAB application package ver. R2017a was used as the computing runtime environment. During the experiments, we estimated the weights values of the features using the NCA algorithm. The results of calculations are presented graphically in figure 1.



**Figure 1.** The feature weights

Figure 2 shows the dependence of the number of features on the weight threshold value, which was calculated in accordance with the formula for the terms of the geometric progression:

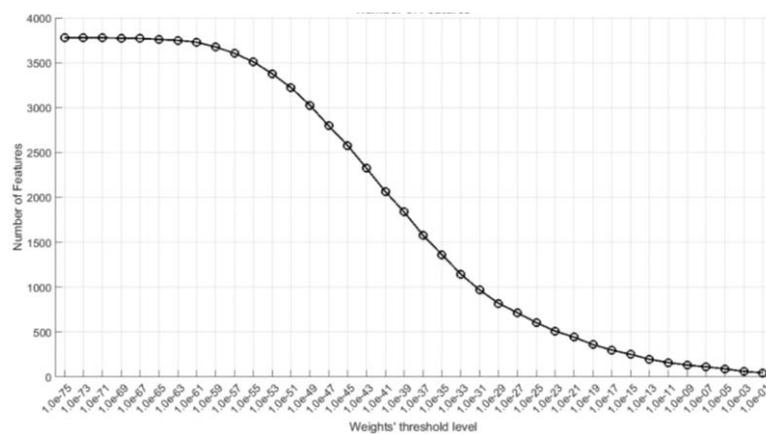
$$Q_n = 10^{-75} \cdot 100^{n+1}.$$

In accordance with the approach proposed by the authors of the HOG descriptor, a linear SVM classifier was trained. A herewith, only features that crossed the threshold  $Q_n$  participated in this training. Figure 3 shows the number of errors in the training and test sets with an increase in the weight threshold value, and as a result, with a decrease in the number of the considered features. The analysis of this figure allows to say that with a decrease in the number of the considered features, the large number of errors appear in the training set, which means the set becomes linearly inseparable. At the same time, with a small threshold value, that is, with a small filtering out of the features of objects,

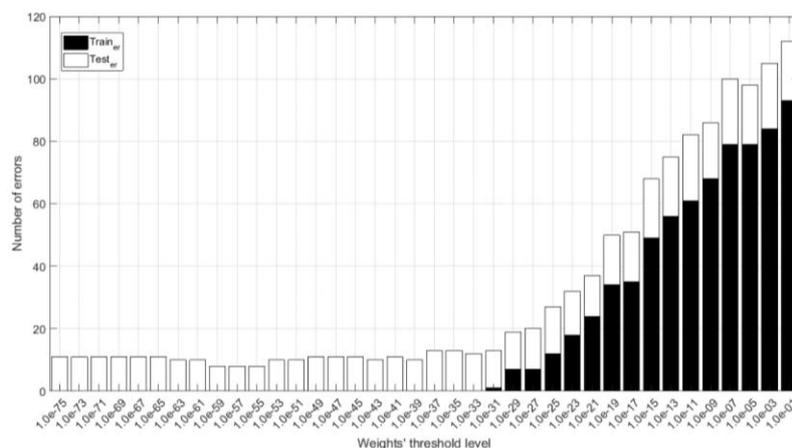
there is the acceptable generalizing ability of the trained model, consisting in a small number of errors in both the training and test sets.

**Table 1.** The characteristics of the experimental dataset

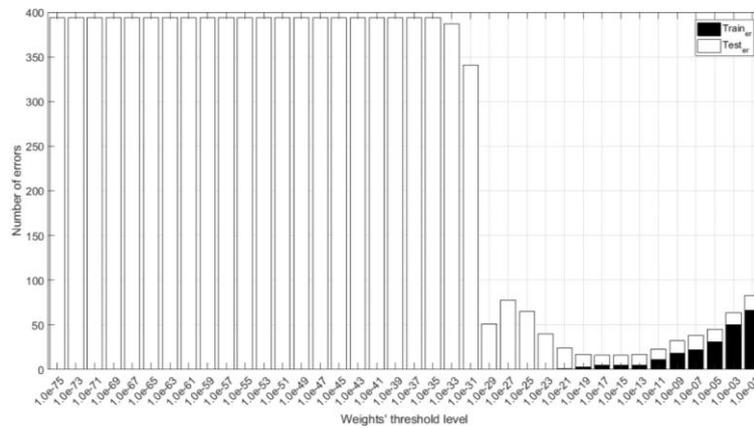
Feature	Value
The number of objects in the experimental data set	4172
The number of objects of class “+1” (that is, the number of targets)	2172
The number of objects of class “- 1” (that is, the number of objects of the background)	2000
The proportion of the test set in the experimental dataset	0.2
The number of objects in the training set	3338
The number of objects in the test set	834



**Figure 2.** The dependency of the number of features from the threshold weight for the linear kernel function

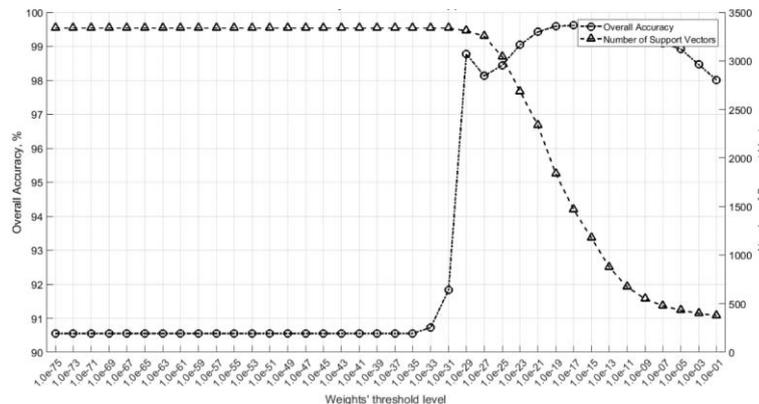


**Figure 3.** The dependency of the number of errors in the training and test sets from the threshold weight for the linear kernel function

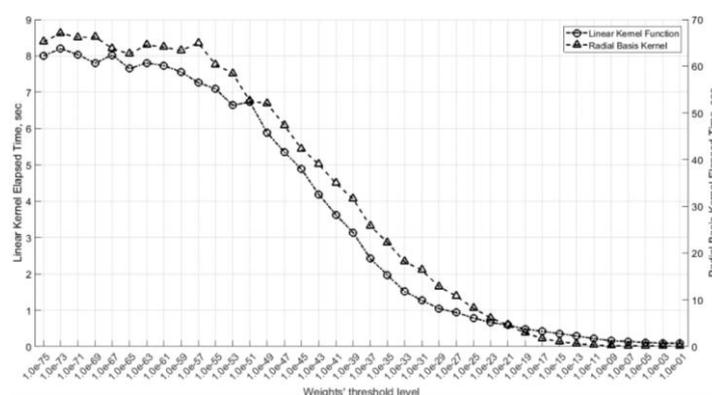


**Figure 4.** The dependency of the number of errors in the training and test sets from the threshold weight for the radial basis kernel function

Based on the assumption that the set becomes linearly inseparable, it was decided to train the SVM classifier with the nonlinear kernel function, namely, with the radial basis kernel function. The learning results are presented in the same format as for the linear kernel function in figure 4. With a small threshold, there is an obvious re-training of the model, which is characterized by a small number of errors in the training set and a large number of errors in the test set. Indeed, the corresponding number of support vectors (figure 5) for the analyzed range of weights indicates the unsatisfactory generalizing ability of the model and the obvious retraining.



**Figure 5.** The dependencies of the overall accuracy and the number of support vectors from the threshold weight for the radial basis kernel function



**Figure 6.** The dependency of the development time for the linear and nonlinear SVM classifiers from the number of the considered features of objects

On the basis of the obtained results, the following conclusion can be drawn: as the number of the considered features decreases in accordance with the weights obtained by the feature selection algorithm, the training set becomes linearly inseparable. The transition from the linear separability to the linear inseparability for the considered example is observed for the threshold value within the range from  $1E-29$  to  $1E-17$ . The number of features decreases from 819 to 298. It should be noted that, for example, the results of the nonlinear SVM classifier at the threshold which equals to  $1E-17$ , when the number of the considered features is 298, are not inferior to the results of the linear SVM classifier trained on the entire set of features.

Figure 6 shows the dependency graphs of the learning time for the linear and nonlinear SVM classifiers. The time of learning of the linear SVM classifier with the entire feature set was equal to 8 seconds. The time of learning of the nonlinear SVM classifier with the threshold weight value which equals to  $1E-17$  was equal to 1.7 seconds.

The studies conducted on the considered dataset prove the feasibility of reducing the number of features. The open libraries of machine learning and computer vision use much larger datasets for learning. When forming these datasets, some initial set of images containing objects of classes is subject to various distortions. The purpose of such distortions is an attempt to provide for various options for the location and shape of some object in the image. In this case, the distortion affects the number of informative features. It should be noted that the main goal of the open libraries developers is to develop the universal tools for solving detection problems that meet the most frequent requirements of users. However, if the goal is to develop a proprietary software solution for working in the specific conditions and with the common format for representation of the objects classes, it is necessary to consider the possibility of accelerating both the calculation of the histogram of the oriented gradients and the development of the SVM classifier, which was shown in this experimental study.

#### 4. Conclusion

Experimental studies have confirmed the high efficiency of application of the special tool known as the feature selection using the neighborhood component analysis algorithm for classification to determine the most informative features of objects. It is shown that this tool allow to reduce the time expenses on solving the objects detection problem while maintaining acceptable values of the classification quality indicators.

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