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SIMPLE OBJECTS DETECTION AND RECOGNITION BY THE PROBABILISTIC APPROACH

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Abstract

Purpose: *The represented research results are aimed to better understanding of computer vision methods and their capabilities. The statistical approach of object detection and recognition allows processing of typical objects with simple descriptors.* ***Methods:*** *Considered approach is grounded at probabilistic methods, kernel density estimation and computer-based simulation as a verification tool.* ***Results:*** *Considered approach for object detection and recognition has shown several advantages in comparison with existing methods due to its simple realization and small time of data processing. Presented results of experimental verification prove that the considered method can be applied for detection and classification of objects with various shapes.* ***Discussion:*** *The approach can be implemented in a variety of computer vision systems that observe objects in difficult noisy conditions.*

Keywords: Bayesian approach; object detection; probability density function; recognition.

1. Introduction

Pattern recognition is one of the biggest task fields of machine learning and computer vision. Its main purpose is detection and recognition of any specific objects or regular patterns in images or video data. Computer vision founds more and more applications in such areas as security systems, quality control in production, document processing, automatic vehicle navigation, image processing, medical decision support systems, remote sensing, etc. [1,2].

Pattern recognition is the technique that makes machine able to understand the environment and discriminate different patterns, and to make various types of decisions based on the environment observation [3]. There are two main divisions of classification according to the type of learning used to generate the output value: the supervised classification (discrimination) and the unsupervised classification (usually, called simply as classification or clustering). In the supervised classification, there are the training data samples with associated labels for corresponding class of pattern or object. In the unsupervised classification, the data are not labeled, and the classification algorithm has to find separate groups in the data and features that distinguish one group from another. Sometimes the mixed semi-supervised learning is utilized for better results. It uses a combination of labeled and unlabeled data for the classification [1].

2. Analysis of the research and publications

Due to the importance and variety of problems, which can be solved by pattern recognition, there have been discovered many methods. Based on [1], one can do the following classification of main pattern recognition methods:

– statistical pattern recognition,
– artificial neural networks,
– sparse kernel machines.

Statistical pattern recognition assumes the use of statistical techniques for analyzing measured data, information extraction, and decision making. Its task is to find, learn, and recognize patterns in complex data, for example in images, speech, biological pathways, and the Internet. Various models were proposed and used in recent publications, e.g., linear, logistic or basis function regression, Hidden Markov Model, etc. [2]

Statistical methods include estimation of the distributions of pattern feature vectors with and without objects of interest, and then apply a pattern classifier or an object detector to search over a range of other parameters that have influence on observed distributions. In this way the invariance to some unavoidable conditions is achieved. Specifically to statistical methods, the supervised classification assumes the knowledge of a probability density function (PDF) for each class of objects. Of course, in most real situations those PDFs are unknown and have to be estimated from a set of training samples with a correct label of each class.

3. Aim of the paper

The goal of the article is to analyze and verify the proposed earlier Bayesian approach for object detection and recognition on an example with graphics primitives.

4. Bayesian approach for object detection and recognition

We assume that N classes of objects are given. They correspond to prior probabilities $p_1,\dots,p_N$, with

$$p_i>0,\ i=\overline{1,N},\ \sum_1^N p_i = 1.$$

If there is a vector signal $\xi\in\Re^q$ from the object of ith class, it is described with a probability density function (pdf) $\rho_i(x;\theta)$, $x\in\Re^q$, $\theta\in\Theta\subset\Re^d$.

Here θ is a parameter that sets the observation conditions, such as certain angles associated with object; Θ is a parameter set for θ, i.e., a set where θ can vary. We suppose that the parameter θ is known exactly.

If none of the classes is observed, then the signal ξ has a pdf $\rho_0(x;\theta)$. It corresponds to the probability distribution of noise which contains a useful signal from neither object of neither class [5, 6].

We check the null hypothesis H_0: an object belonging to one of the abovementioned classes is observed, vs. an alternative hypothesis H_1: a pure noise is observed. Consider a test statistic

$$T_n = \prod_{k=1}^{n}\frac{\bar\rho(x_k;\theta_k)}{\rho_0(x_k;\theta_k)}.$$

Here

$$\bar\rho(x;\theta)=\sum_{i=1}^{N} p_i\rho_i(x;\theta)$$

denotes a weighted pdf of the signal. We suppose that α and β are given levels for a Type I error (the probability to reject H_0 under true H_0) and a Type II error (the probability to accept H_0 under true H_1).

We choose thresholds as

$$A=\frac{1-\beta}{\alpha}\ ,\ B=\frac{\beta}{1-\alpha}\ .$$

We continue observations until one of the inequalities holds true:

$$T_n \ge A \quad \text{or} \quad T_n \le B.$$

In the first case, H_0 is accepted (an object is detected), and in the second case, H_0 is rejected (an object is not detected).

In practice, rarely there is any information about a probability distribution of required parameters. Therefore, some kind of estimates must be used in the equation for the test statistic instead of determined function values. We consider the kernel density estimates [7]. For this purpose we use the Epanechnikov kernel that is preferable over the Gaussian one due to absence of exponent and possible extremely large or small numbers.
The kernel density estimator is evaluated by observations as

$$\hat f_n(x)=\frac{1}{nh_1\dots h_d}\sum_{i=1}^{n}\prod_{j=1}^{d}K\Big(\frac{x_j-X_{ij}}{h_j}\Big),$$

where $x=(x_1,\dots,x_d)\in\Re^d$; h_j, $j=\overline{1,d}$, is a bandwidth for jth parameter. In order to choose h_j, $j=\overline{1,d}$, the cross-validation cost function is defined:

$$\hat J(h)=\int_{\Re^d}\hat f_n^2(x)dx-\frac{2}{n}\sum_{i=1}^{n}\hat f_{-i}(X_{-i})\ ,$$

$$h=(h_1,\dots,h_d)\in(0,+\infty)^d\ .$$

Here $\hat f_{-i}$ is the kernel density estimate constructed by the set of observations X_{-i} obtained from the total observation set after deleting the observations $X_{i,j}$, $j=\overline{1,d}$, which correspond to the time moment i. Then the asymptotically optimal estimate equals

$$\hat h := \underset{h>0}{\arg\min}\,\hat J(h)\ .$$

Suppose that an object has been detected. We continue the observations and receive new data

$$x_n,\dots,x_m\ ,\ \theta_n,\dots,\theta_m\ ,\ m\ge n\ .$$

Here we use the observation x_n which was received at the moment of recognition algorithm termination, and new observations as well.

Posterior probabilities can be evaluated as follows:

$$q_k^{(m)}=\frac{p_k\rho_k(x_n;\theta_n)\rho_k(x_{n+1};\theta_{n+1})\dots\rho_k(x_m;\theta_m)}{\sum_1^N p_i\rho_i(x_n;\theta_n)\rho_i(x_{n+1};\theta_{n+1})\dots\rho_i(x_m;\theta_m)},$$

with $k = 1,..., N$.

The observations can be terminated if the following condition holds true:

$$\max_{1 \le k \le N} q_k^{(m)} \ge P_C .$$

Here P_C is a probability of correct recognition. If in this inequality we have “strictly less” sign, then we continue observations until the termination condition is fulfilled. After the termination, the hypothesis H_j about belonging the object to jth class is accepted if

$$q_j^{(m)} = \max_{1 \le k \le N} q_k^{(m)} .$$

Since P_C>0.5, the accepted hypothesis is uniquely defined.

5. Discriminative features

Finding the correspondences between images with the same or similar objects, but taken from different sources or under different conditions is one of the most important tasks in image processing and computer vision. The idea of extracting a set of features of the desired object or pattern from the image, and describe each of them by the unique signature (descriptor), so that it can be automatically found again in other images by its signature, is the most popular approach for image recognition.

There are many requirements for a good feature descriptor. For example, it must be invariant to the complex changes of context and objects properties. It also has to be compact, fast to compute, and capable to encapsulate as much descriptive information as possible.

Among more complicated descriptors, there are ‘classic’ ones such as SIFT and SURF. They have been known as two of the most popular and successful feature descriptors which can be applied in many applications, from image registration to object recognition [8]. However, in many situations they are too excessive and can be replaced by a set of simple statistical parameters. In this paper, we consider such parameters as the eigenvalues of the covariance matrix and its first eigenvalue in particular, that describe the object’s shape. Also such statistical values by each axis as a skewness and an excess kurtosis are defined. They describe shapes of brightness distribution.

6. Simulation results

The performance of the considered algorithm was tested on the basic set of filled objects represented by 5 graphics primitives that are shown in Fig. 1. For test purposes they were drawn separately and then imported in MATLAB where they were transformed accordingly to specified parameters and polluted by simulated noise. Hereafter they are processed as two-dimensional arrays.

All objects have the same extents, placed in the center of the observation window and have a fixed rotational angle.

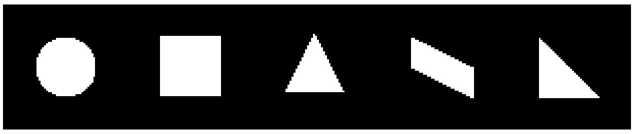

Fig. 1. The set of simulated objects shapes

The simulations were carried out via Monte-Carlo method with the next general parameters and conditions: number of independent iterations 1,000; there were simulated grayscale images with size 64x64 pixels with the bit depth 8bit per pixel; five classes of filled objects (circle, square, parallelogram, isosceles (not right) triangles, and right triangles) with size 32x32 pixels have been randomly placed in the center of each image with equal probabilities, on three basic descriptors: first eigenvalue of the correlation matrix, skewness and the excess kurtosis by the x axis; signal-to-noise ratio SNR=0dB, training sample size for each class of objects N=100, maximal number of available observations for detection and recognition is limited by the training sample size, probabilities of false alarm and missing object are α, β =0.01; classification threshold $P_c = 0.99$; object brightness is set to 127 with the maximum brightness value 255, object to background brightness ratio is 1/4.

A few criterions of effectiveness have been considered: detection probability, correct classification probability, and number of observations when the object was detected and classified. Simulations have shown than in these conditions the method provided 100% detection probability in most cases except some situations with extremely strong noise. Classification probability is on the expected level as well. Therefore, plots for them are not shown here.

Fig. 2 shows plots of average number of observation at which detection and classification have been done for various signal to noise ratios.

It shows that the detector works well in a wide range of SNR, and even in severe noise conditions a single observation is enough. That can be explained by the fact that the distance between features classes with and without objects is big enough for brief detection of object presence. On the other hand, the recognition procedure significantly drops at 5dB. Also there has been simulated the case for dependencies by the number of used criterions. Corresponding plots are shown in Fig. 3. It is well visible that sufficient performance is achieved when 4 features are used for the classification.

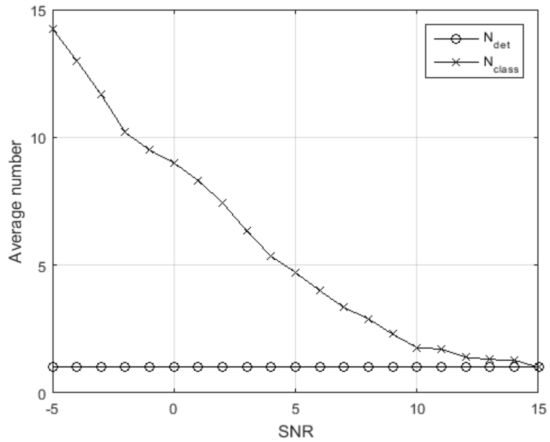

Fig. 2. Performance criterions plots at various SNR

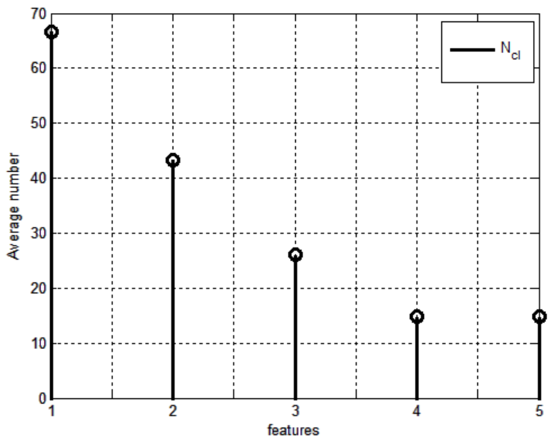

Fig. 3. Average number of observations at various features numbers

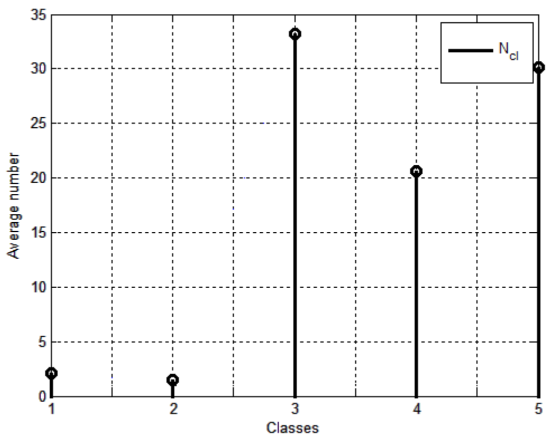

Fig. 4. Average number of observations required for classification of each class of objects

Additionally it has been estimated the complication of classification of each class. Fig. 4 represents average number of observations for recognition of each class of objects (1 – circle, 2 – square, 3 – isosceles triangle, 4 – parallelogram, 5 – right triangle)

It shows that such objects like a circle or a square are classified almost instantly, while triangular objects require much more observations.

8. Conclusions

The considered Bayesian approach to object detection and recognition for images processing has several advantages such as its simple realization, short time of processing and high level of object recognition. Presented simulation results prove that the considered method can be applied for detection and classification of objects with various shape.

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Виявлення та розпізнавання простих об’єктів з використанням імовірнісного підходу

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Мета: Представлені результати досліджень спрямовані на краще розуміння методів комп’ютерного зору та їхніх можливостей. Статистичний підхід до виявлення та розпізнавання об'єктів дозволяє обробляти типові об’єкти з простими дескрипторами. **Методи дослідження:** Розглянутий підхід базується на методах теорії ймовірності, ядерній оцінці щільності ймовірності та комп'ютерному моделюванні як засобі апробації. **Результати:** Розглянутий підхід до виявлення та розпізнавання об'єктів продемонстрував ряд переваг у порівнянні з існуючими методами завдяки простоті реалізації та швидкій обробці даних. Представлені результати експериментальної перевірки доводять, що розглянутий метод може використовуватись для виявлення та розпізнавання об’єктів різної форми. **Обговорення:** Підхід може бути реалізований у багатьох системах комп’ютерного зору, що оглядають об’єкти в складних шумових умовах.

Ключові слова: Байєсівський підхід; виявлення об'єкту; розпізнавання; щільність імовірності.

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Обнаружение и распознавание простых обьектов с помощью вероятностного подхода

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Цель: Представленные результаты исследований направлены на лучшее понимание методов компьютерного зрения и их возможностей. Статистический подход к выявлению и распознаванию объектов позволяет обрабатывать типовые объекты с простыми дескрипторами. **Методы исследования:** Рассматриваемый подход базируется на методах теории вероятности, ядерном оценивании плотности вероятности и компьютерном моделировании как средстве апробации. **Результаты:** Рассматриваемый подход к обнаружению и распознаванию объектов продемонстрировал ряд преимуществ по сравнению с существующими методами благодаря простоте реализации и быстроте обработки данных. Представленные результаты экспериментальной проверки показывают, что данный метод может быть использован для обнаружения и распознавания объектов различной формы. **Обсуждение:** Подход может быть реализован во многих системах компьютерного зрения, которые осматривают объекты в сложных шумовых условиях.

Ключевые слова: Байесовский подход; обнаружение обьекта; плотность вероятности; распознавание.

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