UDC629.735.05 (045)
DOI: 10.18372/2306-1472.80.14268

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FOREGROUND DETECTION IN DYNAMIC SCENES OF INTELLIGENT TRANSPORT SYSTEMS

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Abstract

The paper considers aspects of foreground detection in dynamic scenes of intelligent transport system based on computer vision and artificial intelligence. Traditional and recent background modeling models have been considered. Nonparametric approach for background subtraction based on the kernel model was used as the most appropriate in dynamic environment. The value of the estimated kernel density function for each pixel of original image was compared with threshold value, estimated by Otsu's method. The proposed kernel density estimation method was verified on video-stream containing moving objects and indicated good performance for Unmanned Aerial Vehicles application.

Keywords: intelligent transport system; kernel density estimation; foreground; background; video stream

1. Introduction

Intelligent Transport Systems (ITS) involve a wide range of technological and organizational systems, applications and services. They play an important role in shaping future ways of mobility and the transport sector.

According to [1], it is expected that through the use of ITS applications transport will become more efficient, safer and greener. The United Nations Economic Commission for Europe (UNECE) focused on ITS as a valuable technology-driven instrument able to boost the future of the transport systems.

The core objective of the UNECE strategy on ITS, is to lobby for new actions and policies where ITS improve the quality of life and make sustainable mobility available across borders.

ITS solutions utilize advanced information technologies related to driver assistance, traffic management, and vehicle control, which are constantly improving the quality of interaction between highway systems and vehicles.

Many institutions and stakeholders consider the deployment of ITS to be a key opportunity for transport policymakers in terms of delivering seamless and efficient customized transport solutions across large areas.

According to a definition from the Research and Innovative Technology Administration, ITS is made up of 16 types of technology-based systems. According to this classification, these systems can be further divided into the subcategories "intelligent infrastructure" and "intelligent vehicle".

Intelligent infrastructure includes:
- Arterial management;
- Freeway management;
- Crash prevention and safety;
- Road weather management;
- Roadway operations and maintenance;
- Transit management;
- Traffic incident management;
- Emergency management;
- Electronic payment and pricing;
- Traveler information;
- Information management;
- Commercial vehicle operations;
- Intermodal freight.

Intelligent vehicle includes:
- Collision avoidance;
- Driver assistance;
- Collision notification.

ITS is a system that integrates information and communication technology with transport infrastructure, vehicles and the user [4].

ITS applications exploit data collected from vehicles to improve the use of vehicles, the safety and comfort of drivers and to rationalize the use of public infrastructures. ITS applications can be categorized into four main classes: infotainment and comfort; traffic management; road safety; and autonomous driving applications.

ITS in aerospace engineering are considered as intelligent systems that use information and communication technologies in the management of aerospace and infrastructure facilities, focused on improving the safety and efficiency of the transport process, comfort for transport users [3].

An aerospace ITS has the following functions:

- Prevention of collision aircraft in airspace and outer space;
- Prevention collision aircraft on ground;
- Preventing collisions aircraft with Earth;
- Ensuring optimum performance of each aircraft flight;
- Providing crew piloted aircraft actual flight information;
- Identification of aircraft for defense purposes;
- Activities associated with the rationalization of air traffic flow;
- Ensuring alerting service and assistance during events for search and rescue.

Continuous image flow is one of the most important sources in ITS. Fixed or portable cameras can provide effective image capturing. Currently, Unmanned Aerial Vehicles (UAVs) are often used as an effective monitoring systems for vehicle detection and tracking. The UAV's computer vision allows getting images in different situations and from different angles, interpreting and making their sense [5, 7].

Computer vision is the broad domain of artificial intelligence (AI) and can be thought of as the branch of visual sensing, perception, and reasoning within the field of AI.

Thus, the main purpose of the paper is to analyze existing background subtraction models and to research non-parametric approach for background subtraction based on the kernel model for usage in dynamic environment.

2. Background subtraction models

Foreground detection is a key step in many computer vision applications [2]. This step is concerned with the detection of changes or potential objects in the image sequence. The foreground represents the objects that are not stationary in the scene for a period of time. In ITS, foreground detection ultimately aims to identify potential objects called "foreground" from the static information called the "background" [6]. In the dynamic and real-time environment of an ITS, foreground estimation becomes more challenging due to noise, illumination changes, weather conditions, and a cluttered environment [11]. Therefore, the background representation model must be reliable, robust and adaptive for sudden or gradual changes in the scene.

The classification of background modeling models is represented in the Table [8].

Table

Classification of background modeling models

Background Modeling Models	Categories	Sub-Categories
Traditional Models	Basic Models	Mean, Median, Histogram, Pixel Intensity Classification, Pixel Change Classification
	Statistical Models	Gaussian Models (single Gaussian, general Gaussian, mixture of Gaussians, mixture of general Gaussians, Kernel Density Estimation), Support Vector Models, Subspace Learning Models
	Clusters Models	K-means, Codebook, Basic Sequential Clustering
	Neural Networks	General Regression, Multivalued, Competitive, Dipolar Competitive, Self-Organizing, Growing Hierarchical Self-Organizing, Adaptive Resonance Theory Neural Network
	Estimation Models	Wiener filter, Kalman filter, Correntropy filter, Chebychev filter
Recent Models	Advanced Statistical Models	Mixture Models, Hybrid Models, Non Parametric Models, Co-occurrence, Multi-Kernels
	Fuzzy Models	Fuzzy C-means Clustering
	Discrimi-native and Mixed Subspace Models	Incremental Maximum Margin Criterion
	Kernel Subspace Models	Kernel Principal Component Analysis

End Table

Background Modeling Models	Categories	Sub-Categories
	Robust Subspace Models	Principal Component Analysis, Half-Quadratic-PCA, Pursuing Dynamic Spatio-Temporal Models 1) Robust Principal Components Analysis (RPCA) 2) Robust Non-negative Matrix Factorization (RNMF) 3) Robust Orthonormal Subspace Learning (ROSL)
	Subspace Tracking	Grassmannian Robust Adaptive Subspace Tracking Algorithm, Robust Subspace Tracking, Grassmannian Online Subspace Updates with Structured-sparsity
	Low-Rank Minimiza-tion	Detecting Contiguous Outlier detection in the Low-rank Representation, Direct Robust Matrix Factorization, Probabilistic Robust Matrix Factorization, Bayesian Robust Matrix Factorization
	Sparse Models	Dynamic Group Sparsity, Dictionary Learning, Sparse Error Estimation
	Robust Tensor Models	Robust Principal Components Analysis Tensor, Nonnegative matrix factorization Tensor
	Outlier Detection	Local Outlier Factor, Connectivity-based Outlier Factor
	Transform Domain Models	Walsh, Wavelet, Hadamard

Kernel density estimation (KDE) method is a non-parametric approach allowing construction of a function that gives the probability that a given image pixel belongs to the distribution of background pixels [9, 12, 13].

In the kernel density estimator, the distribution is constructed from a sum of kernels [10,14].Therefore, usage of KDE is effective technique for background subtraction in dynamic environment and could be used for UAV video processing.

3. Kernel density estimation

Uniform, triangle, Epanechnikov, quartic, triweight, Gaussian, cosine, logistic or sigmoid functions could be used as a kernel density, depending on background representation.

In our research, we use Gaussian kernel model for observed vectors $X_i=(X_{i1},\ldots, X_{id})$, $i=1,\ldots,n$ of dimension d.

They are independent, identically distributed random vectors with certain probability density function $f(x)$. Its kernel density estimator is as follows

$$\hat{f}_n(x)=\frac{1}{n\sigma_1\ldots\sigma_d}\sum_{i=1}^{n}\prod_{j=1}^{d}K\left(\frac{x_j-X_{ij}}{\sigma_j}\right),\quad x=(x_1,\ldots,x_d)\in\Re^d, \quad (1)$$

where σ_j is the bandwidth for jth coordinate.

We define the optimal bandwidth as

$$\sigma_{jopt}=\left(\frac{4\mu_k}{\sigma_k^4\int\limits_{\Re^d}\left|\nabla^2 f(x)\right|^2dx}\cdot\frac{1}{n}\right)^{\frac{1}{d+4}},\ j=1,\ldots,d, \quad (2)$$

$$\sigma_k^2=\int\limits_{\Re^d}\|x\|^2K(\|x\|)dx=E\sum_{i=1}^{d}\gamma_i^2=\sum_{i=1}^{d}D\gamma_i=d, \quad (3)$$

$$\nabla^2 f=\sum_{i=1}^{d}\frac{\partial^2 f}{\partial x_i^2}, \quad (4)$$

where $\gamma_1,\ldots,\gamma_d$ are independent standard normal variables. Thus,

$$\sigma_k^4=d^2; \quad (5)$$

$$\mu_k=\int\limits_{\Re^d}K^2(\|x\|)dx=\prod_{1}^{d}\int\limits_{\Re}\frac{1}{2\pi}e^{-x_k^2}dx_k=\left(\frac{1}{2\pi}\sqrt{\pi}\right)^d=\left(\frac{1}{2\sqrt{\pi}}\right)^d. \quad (6)$$

Here we use the Euler–Poisson integral

$$\int\limits_{\Re}e^{-x^2}dx=\sqrt{\pi}.$$

True density $f(x)$ is unknown, therefore, we use the adaptive estimator of the bandwidth:

$$\hat{\sigma}_{jopt}=\left(\frac{4\mu_k}{\sigma_k^4\int\limits_{\Re^d}\left|\nabla^2\hat{f}_n(x)\right|^2dx}\cdot\frac{1}{n}\right)^{\frac{1}{d+4}}. \quad (7)$$

Preliminary estimation of $\hat{f}_n$ is done using the bandwidth evaluated as

$$\sigma_1^*=\sigma_2^*=\ldots=\sigma_d^*=\left(\frac{4}{(d+2)n}\right)^{\frac{1}{d+4}}. \quad (8)$$

We evaluate the integral in (7) as follows:

$$J = \int\limits_{\Re^d} \left|\nabla^2 \hat{f}_n(x)\right|^2 dx \qquad (9)$$

,

$$J = \frac{1}{n^2\sigma_*^{2d+4}} \sum_{i',i''=1}^{n} \int\limits_{\Re^d} \prod_{j=1}^{d} K\left(\frac{x_j - X_{i'j}}{\sigma_*}\right) K\left(\frac{x_j - X_{i''j}}{\sigma_*}\right) \times$$
$$\times \left(\sum_{k=1}^{d}\left(\frac{x_k - X_{i'k}}{\sigma_*}\right)^2 - d\right)\left(\sum_{k=1}^{d}\left(\frac{x_k - X_{i''k}}{\sigma_*}\right)^2 - d\right) dx_1 ... dx_d .$$

Let's make a change of variables under the integration sign:

$$x_j - \frac{X_{i'j} + X_{i''j}}{2} = t_j \cdot \qquad (10)$$

$$J = \frac{1}{n^2\sigma_*^{2d+4}} \sum_{i',i''=1}^{n} \int\limits_{\Re^d} \prod_{j=1}^{d} \frac{1}{2\pi} e^{\frac{-t_j^2}{\sigma_*^2}} e^{\frac{-(X_{i'j}-X_{i''j})^2}{4}} \times$$
$$\times \left(\sum_{k=1}^{d}\left(t_k + \frac{X_{i''k} - X_{i'k}}{2}\right)^2 \frac{1}{\sigma_*^2} - d\right)\left(\sum_{k=1}^{d}\left(t_k + \frac{X_{i'k} - X_{i''k}}{2}\right)^2 \frac{1}{\sigma_*^2} - d\right) dt_1 ... dt_d \qquad (11)$$

Denote

$$\Delta_{i'i''j} = \frac{X_{i''j} - X_{i'j}}{2} .$$

Then

$$J = \frac{1}{n^2\sigma_*^{2d+4}} \sum_{i',i''=1}^{n} e^{-\sum_{j=1}^{d}\Delta_{i'i''j}^2} \frac{1}{(2\pi)^d} \int\limits_{\Re^d} \prod_{j=1}^{d} e^{\frac{-t_j^2}{\sigma_*^2}} \times$$
$$\times \left(\sum_{k=1}^{d}(t_k + \Delta_{i'i''k})^2 \frac{1}{\sigma_*^2} - d\right)\left(\sum_{k=1}^{d}(t_k - \Delta_{i'i''k})^2 \frac{1}{\sigma_*^2} - d\right) dt_1 ... dt_d . \qquad (12)$$

To interpret the integrals in (12) in a probabilistic sense, we make a substitution:

$$\frac{t_j^2}{\sigma_*^2} = \frac{u_j^2}{2},\ u_j = \frac{\sqrt{2}}{\sigma_*} t_j,\ t_j = \frac{\sigma_*}{\sqrt{2}} u_j .$$

Then $dt_j = \frac{\sigma_*}{\sqrt{2}} du_j$,

$$J = \frac{1}{n^2\sigma_*^{d+4}} \sum_{i',i''=1}^{n} e^{-\sum_{j=1}^{d}\Delta_{i'i''j}^2} \frac{1}{(2\sqrt{2}\pi)^d} \int\limits_{\Re^d} e^{\frac{-\|u\|^2}{2}} \times$$
$$\times \left(\sum_{k=1}^{d}\left(\frac{\sigma_*}{\sqrt{2}} u_k + \Delta_{i'i''k}\right)^2 \frac{1}{\sigma_*^2} - d\right)\left(\sum_{k=1}^{d}\left(\frac{\sigma_*}{\sqrt{2}} u_k - \Delta_{i'i''k}\right)^2 \frac{1}{\sigma_*^2} - d\right) du$$

;

$$J = \frac{1}{4n^2\sigma_*^{d+4}(2\sqrt{\pi})^d} \sum_{i',i''=1}^{n} e^{-\sum_{j=1}^{d}\Delta_{i'i''j}^2} \frac{1}{(\sqrt{2\pi})^d} \int\limits_{\Re^d} e^{\frac{-\|u\|^2}{2}} \times$$
$$\times \left(\sum_{k=1}^{d}\left(u_k + \frac{\sqrt{2}}{\sigma_*}\Delta_{i'i''k}\right)^2 - d\right)\left(\sum_{k=1}^{d}\left(u_k - \frac{\sqrt{2}}{\sigma_*}\Delta_{i'i''k}\right)^2 - d\right) du \qquad (13)$$

The function $\frac{1}{(\sqrt{2\pi})^d} e^{\frac{-\|u\|^2}{2}}$, $u \in \Re^d$, is the density of the standard Gaussian vector γ=(γ1,…,γd)Tin $\Re^d$. Its components are independent standard normal random variables. Denote

$$W_{i'i''k} = \frac{\sqrt{2}}{\sigma_*}\Delta_{i'i''k} \qquad (14)$$

We have

$$J = \frac{1}{n^2\sigma_*^{d+4} 2^{d+2} \pi^{d/2}} \sum_{i',i''=1}^{n} e^{-\sum_j \Delta_{i'i''j}^2} \times$$
$$\times E\left(\sum_{k=1}^{d}(\gamma_k + W_{i'i''k})^2 - d\right)\left(\sum_{k=1}^{d}(\gamma_k - W_{i'i''k})^2 - d\right) \qquad (15)$$

To calculate the latter expectation $M_{i'i''}$, we denote

$$C_{i'i''k} = W_{i'i''k} - 1 ; \qquad (16)$$

$$M_{i'i''} = E\left(\sum_{k=1}^{d}\left(\gamma_k^2 + 2\gamma_k W_{i'i''k} + C_{i'i''k}\right)\right)\left(\sum_{p=1}^{d}\left(\gamma_p^2 - 2\gamma_p W_{i'i''p} + C_{i'i''p}\right)\right)$$

,

$$M_{i'i''} = E\left(\sum_{k,p=1}^{d}\gamma_k^2\gamma_p^2\right) + 2\left(E\sum_{k=1}^{d}\gamma_k^2\right)\left(\sum_{p=1}^{d}C_{i'i''p}\right) -$$
$$-4E\left(\sum_{p}^{d}\gamma_k W_{i'i''k}\right)^2 + \left(\sum_{k=1}^{d}C_{i'i''k}\right)^2 . \qquad (17)$$

We took into account that

$$0 = E\gamma_k^3 = E\gamma_k = E\gamma_k\gamma_p^2, k \neq p.$$

Then

$$E\sum_{1}^{d}\gamma_k^2 = d ,$$

$$E(\sum_{1}^{d}\gamma_k W_{i'i''k})^2 = \sum_{1}^{d} D(\gamma_k W_{i'i''k}) = \sum_{k=1}^{d} W_{i'i''k}^2 ,$$

$$E\sum_{k,p=1}^{d}\gamma_k^2\gamma_p^2 = E\sum_{1}^{d}\gamma_k^4 + E\sum_{k\neq p}^{d}\gamma_k^2\gamma_p^2 = 3d + d(d-1) = d(4d-1)$$

Here we used that $E\gamma_k^4 = 3$, and for $k \neq p$,

$$E\gamma_k^2\gamma_p^2 = (E\gamma_k^2)(E\gamma_p^2) = 1 .$$

Thus,

$$M_{i'i''} = d(4d-1) + 2d \cdot \sum_{p=1}^{d} C_{i'i''p} - 4\sum_{k=1}^{d} W_{i'i''k}^2 + (\sum_{k=1}^{d} C_{i'i''k})^2$$

,

$$M_{i'i''} = d(4d-1) + 2d\left(\sum_{p=1}^{d}\frac{2}{\sigma_*^2}\Delta_{i'i''p}^2 - d\right) -$$
$$-4\sum_{k=1}^{d}\frac{2}{\sigma_*^2}\Delta_{i'i''k}^2 + \left(\sum_{k=1}^{d}\frac{2}{\sigma_*^2}\Delta_{i'i''k}^2 - d\right)^2 ,$$

$$M_{i'i''} = d(4d-1) + \frac{4(d-2)}{\sigma_*^2}\sum_{k=1}^{d}\Delta^2_{i'i''k} + \frac{4(d-2)}{\sigma_*^4}\left(\sum_{k=1}^{d}\Delta^2_{i'i''k}\right)^2 - \frac{4d}{\sigma_*^2}\sum_{k=1}^{d}\Delta^2_{i'i''k} + d^2,$$

$$M_{i'i''} = d(3d-1) - \frac{8}{\sigma_*^2}\sum_{k=1}^{d}\Delta^2_{i'i''k} + \frac{4}{\sigma_*^4}\left(\sum_{k=1}^{d}\Delta^2_{i'i''k}\right)^2.$$

Now, (15) implies

$$J = \frac{1}{n^2\sigma_*^{d+4}2^{d+2}\pi^{d/2}}\sum_{i',i''=1}^{n} e^{-\sum_j \Delta^2_{i'i''j}} \cdot M_{i'i''} \qquad (18)$$

4. Numerical demonstration

For experimental verification of foreground detection using the KDE model, we used video-stream of traffic data with the purpose to detect movable objects in dynamic environment.

Video duration taken for the experiment is 17 s with a frame rate equal to 30 fr/s. Frame size is 640 pixels in width and 360 pixels in height. The original image is presented in Fig.1.

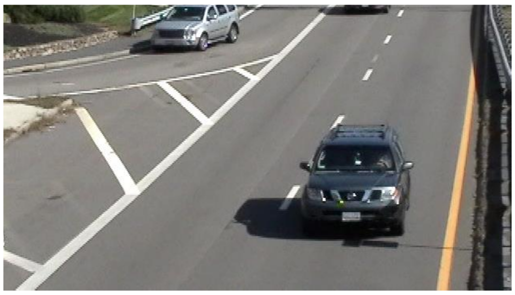

Fig.1. Original image

The kernel density estimate which is constructed by equation (1) for a given image is presented in Fig. 2.

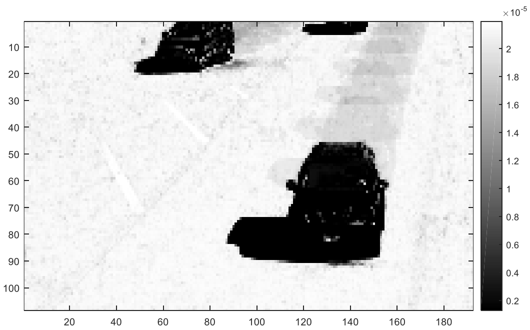

Fig.2. KDE of the original image

The value of the estimated kernel density function for each pixel of original image was compared with threshold value, estimated by Otsu's method [15, 16]. Results of foreground detection are presented in Fig. 3.

Fig.3. Foreground detection on image sequence

Visual analysis of video-stream foreground detection indicates good performance of the proposed KDE model for a dynamic environment. Shadow removal plays a critical role in foreground detection in traffic flow analysis.

Moving shadows in outdoor environments are associated with both moving objects and other objects in the scene. Vehicle shadows will be adjacent to and follow vehicles. Static objects such as trees, signboards, poles, and buildings will cast shadows that move slowly with the movement of the sun. Therefore, efficient shadow removal techniques are also required to ensure a reliable estimation of foreground objects that would be studied in our future research.

5. Conclusions

Background modeling for foreground detection is often used in different applications to model the background and detect the moving objects in the scene for UAV video surveillance. Traditional and recent models of background subtraction have been considered in the paper. KDE as a nonparametric method was selected for foreground detection in UAV video stream data processing. Gaussian function was used as a kernel for estimation. The proposed KDE model was verified on video-stream containing moving objects and indicated good performance for UAV application.

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Виявлення рухомих об'єктів у динамічному просторі інтелектуальних транспортних систем

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У статті розглядаються аспекти виявлення рухомих об'єктів у динамічному просторі інтелектуальної транспортної системи на основі комп'ютерного зору і штучного інтелекту. Були розглянуті традиційні і нові моделі фонового моделювання. Непараметричний підхід для визначення фону, що базується на ядерному оцінюванні, був використаний як найбільш придатний для використання в динамічному середовищі. Значення оціночної функції щільності ядра для кожного пікселя вихідного зображення порівнювалося із граничним значенням, оціненим за методом Оцу. Запропонований метод побудови ядерної оцінки щільності був перевірений на відеопотоці, що містить рухомі об'єкти, і показав прийнятну ефективність для застосування в безпілотних літальних апаратах.

Ключові слова: інтелектуальна транспортна система; ядерна оцінка щільності; рухомі об'єкти; фон; відео потік

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Обнаружение движущихся объектов в динамической пространстве интеллектуальных транспортных систем

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В статье рассматриваются аспекты обнаружения движущихся объектов в динамическом пространстве интеллектуальной транспортной системы на основе компьютерного зрения и искусственного интеллекта. Были рассмотрены традиционные и новые методы фонового моделирования. Непараметрический подход для определения фона, основанный на ядерном оценивании, был использован как наиболее подходящий для использования в динамической среде. Значение оценочной функции плотности ядра для каждого пикселя исходного изображения сравнивалось с пороговым значением, оцененным по методу Оцу. Предложенный метод построения ядерной оценки плотности был проверен на видеопотоке, содержащем движущиеся объекты, и показал хорошую эффективность для применения в беспилотных летательных аппаратах.

Ключевые слова: интеллектуальная транспортная система; ядерная оценка плотности; движущиеся объекты; фон; видео поток

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