

## National Aviation University

# **Application of Artificial Intelligence** in Remotely Piloted Aerial Systems

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The 3<sup>rd</sup> Drone World Congress China, 2019

# Agenda:

- 1. AI and European Strategies
- 2. Multi-parametric data recovery in unmanned aerial system with multi-choice classification of flight situations
- 3. Object detection and classification
- 4. Alternative Positioning, Navigation, and Timing

**Artificial intelligence** (AI) refers to systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals.

**AI-based systems** can be purely software-based, acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g. advanced robots, autonomous cars, drones or Internet of Things applications).

As a scientific discipline, AI includes several approaches and techniques, such as machine learning (of which deep learning and reinforcement learning are specific examples), machine reasoning (which includes planning, scheduling, knowledge representation and reasoning, search, and optimization), and robotics (which includes control, perception, sensors and actuators, as well as the integration of all other techniques into cyber-physical systems)."

Usage of AI may increase anticipatory and decision making capabilities within complex and uncertain environments. AI systems have high potential in ATM, specifically in areas which involves decision making under uncertainty (e.g. conflict detection and resolution) and prediction with limited information (e.g. trajectory prediction).

These approaches can support the human operators in exploitation of timely and dynamic information on atmospheric hazards, traffic fluctuations, and airspace utilisation.

In addition to developing solutions to support en-route operations, AI can be applied in:

- i) speech recognition to act as an additional safety net to detect read-back errors;
- ii) trajectory synchronisation of aircraft ground movements that provide optimised taxiing strategies that comprehensively accounts for arrivals and departures as well;
- iii) predicting the most optimal runway configuration for a given arrival sequence and departure schedule so as to maximise the runway throughput. With the development of these tools, it is envisioned that AI will be integral to ATM operations in the future to form a highly automated environment capable of supporting high intensity and more complex operations. In similar fashion, these decision-making tools also have the potential to ensure that aviation is not held back by human resource constraints.

There is therefore a need to align research, industry, State regulators and service providers to ensure readiness to face and manage an environment where ATM is supported by highly intelligent automation functions that process and generate advisories in a constantly evolving manner that can even adapt to new airspace users such as unmanned aircraft systems (UAS).

Source: Potential of Artificial Intelligence (AI) in Air Traffic Management (ATM). ICAO, Working paper, 2018, 3 p.

Al in Eastern Europe

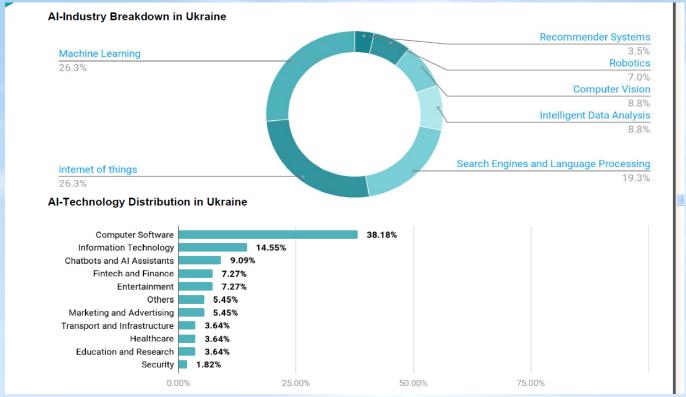




	lumber of Al-Cor	npanies and Investors in Ea	astern Europe	4
	12	Armenia	10	
	47	Belarus	27	
	46	Estonia	27	
	4	Georgia	1	5
se	4	Kazakhstan	2	
Companies	26	Latvia	11	Investors
8	29	Lithuania	5	S
	110	Poland	59	
	32	Romania	1	
	133	Russia	76	
	57	Ukraine	11	

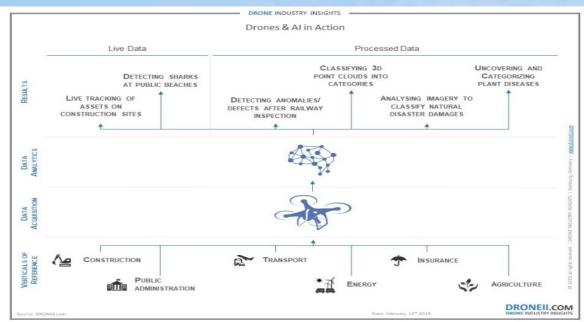
**Source:** Al in Eastern Europe. Artificial Intelligence industry landscape overview 2018. Deep Knowledge Analytics, 2018, 40 p.

### Industry and Technology Distribution in Ukraine (57 Companies)

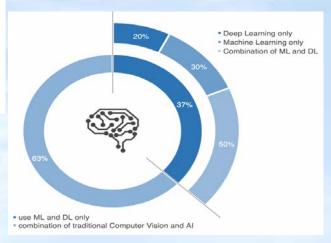


**Source:** Al in Eastern Europe. Artificial Intelligence industry landscape overview 2018. Deep Knowledge Analytics, 2018, 40 p.6

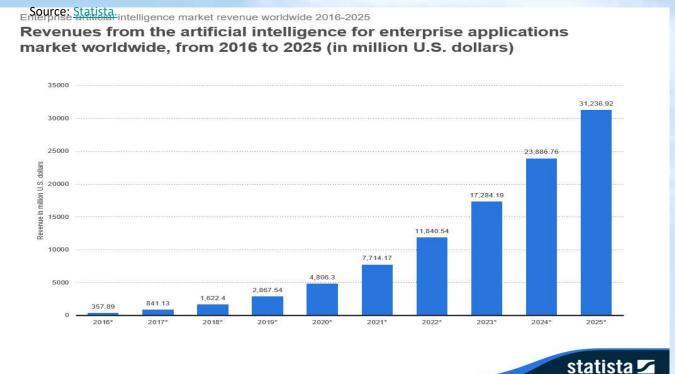
#### **Drones and AI in Action**



**Source:** DRONEII.com



• Global revenues from AI for enterprise applications is projected to grow from \$1.62B in 2018 to \$31.2B in 2025 attaining a 52.59% CAGR in the forecast period. Image recognition and tagging, patient data processing, localization and mapping, predictive maintenance, use of algorithms and machine learning to predict and thwart security threats, intelligent recruitment, and HR systems are a few of the many enterprise application use cases predicted to fuel the projected rapid growth of AI in the enterprise.



#### SESAR STRATEGY

- SESAR-ER4-06-2019: Safety and Resilience
- SESAR-ER4-31-2019: U-space

(Application area: Common altitude reference

Application area: flight-planning and demand and capacity balancing for drones

Application area: U-space separation management service)

- SESAR-ER4-02-2019: Cognitive Support
- SESAR-ER4-09-2019: Legal and Regulatory Challenges of Higher Levels of Automation
- SESAR-ER4-24-2019: Innovation in CNS to enable Digitalised Operations

(Application area: Low cost alternative Position, Navigation and Timing (A-PNT) for General Aviation and drones)



#### **Research problems:**

- Multi-parametric data recovery in unmanned aerial system with multi-choice classification of flight
- ➤ "bad" UAV flight data
- uncertainty of flight situation situations

#### **Research objective:**

To develop a method to recover lost UAV flight data and correct its outliers; to develop method of multi-choice UAV flight situations classification.

#### **Research tasks:**

- To analyze flight data recovering methods; analyze general principles of flight situations classification;
- > To develop a multi-parametric data recovering in Unmanned Aerial System;
- > To improve method of multi-choice UAV flight situations classification considering recovered data;
- > To verify developed methods by means of computer simulation and experimental tests.

#### **Output:**

- > method of multi-parametric data recovery
- > method of multi-choice classification of flight situations



#### **UAS** tendencies

It is predicted in 2022 – 2023 years the period of UAVs commercial sales, their products and services will begin. In subsequent years, a rapid growth in demand for UAVs will be expected to reach 250,000 units up to 2035. 175,000, of which will have commercial application.

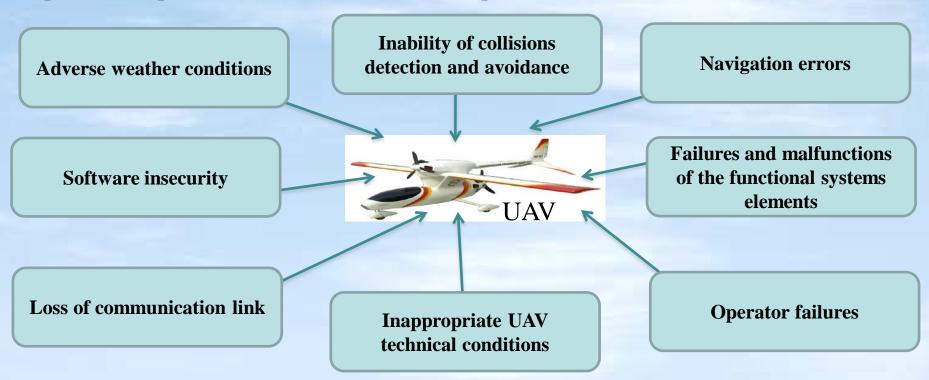


Year

Unmanned Aircraft System. Service Demand 2015 – 2035 / Technical Report, Version 0.1 — September 2013, DOT-VNTSC-DoD-13-01. U.S. Department of Transport. – 2013. – 151 p.

## Factors that affect UAS operation

Flight safety depends on a large number of factors, whose actions are difficult to predict and prevent, since most of them have probabilistic nature.



### Losses and outliers in UAS parameters measurements

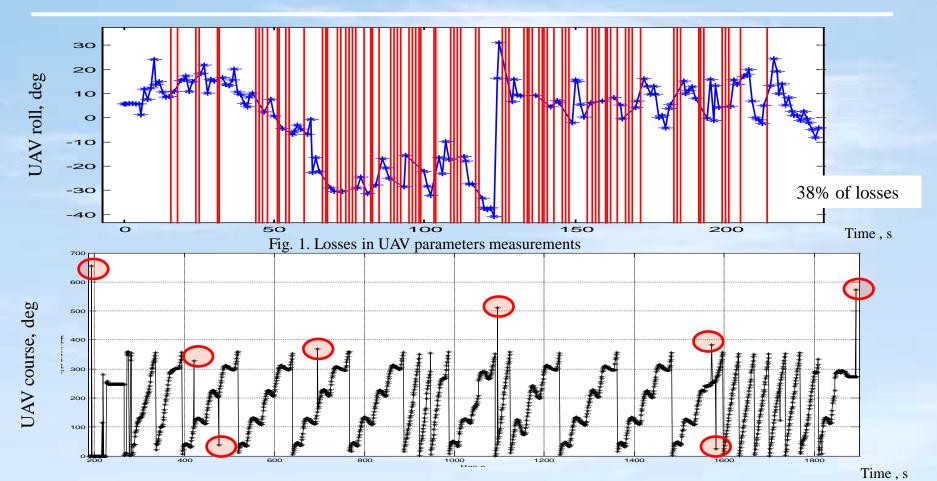


Fig. 2. Outliers in UAV parameters measurements

#### Analysis of lost data recovery methods

#### Lost data recovery methods

#### Common

# Statistical methods of data imputation

- Mean value imputation
- Imputation by constant value
- Imputation by last value
- Imputation by regression
- ZET methods (Zet, ZetM, ZetBraid)
- · Bartlett's method
- Resampling method

#### Methods based on loss nature

\_Expectation-maximization method

Methods based on mathematical model

#### Uncommon

# Methods based on artificial intelligence

- · Cluster analysis method
- Factor analysis method
- Neural network method
- Fuzzy logic method

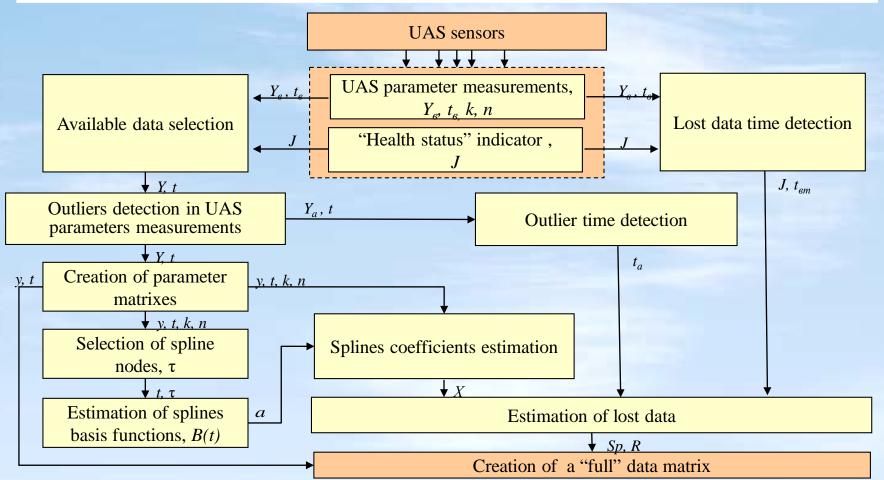
#### **Disadvantages of common methods**

- not universal
- require uniform data
- low precision

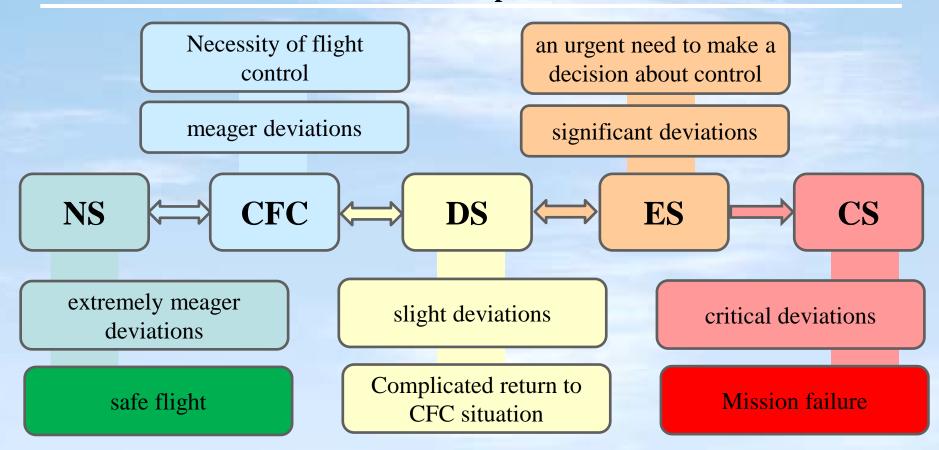
#### Disadvantages of uncommon methods

- complexity of implementation and verification
- rigid hardware requirements
- long computation time

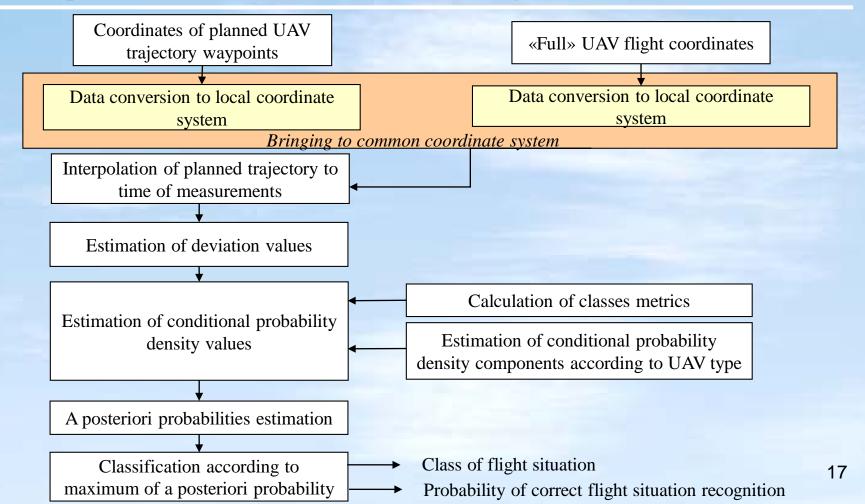
#### Method of Multi-parametric UAS data recovery



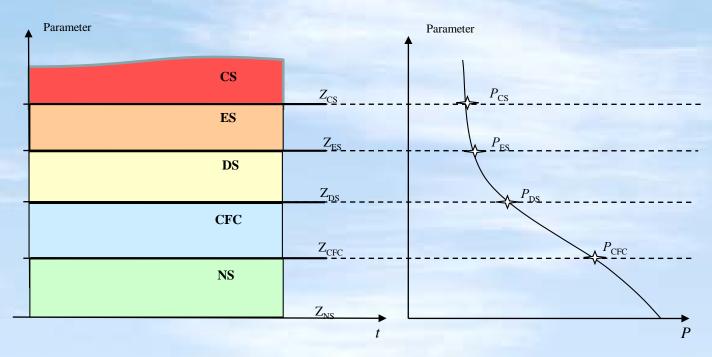
# Representation of multi-choice flight situations classification using the degree of deviation from the planned values



## Improved method of multi-choice UAV flight situations classification



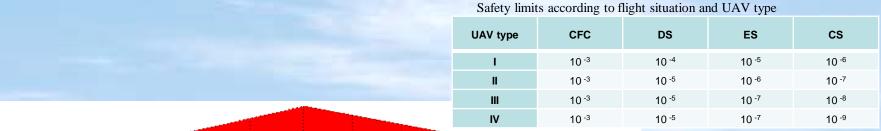
## **Construction of UAV flight situations**

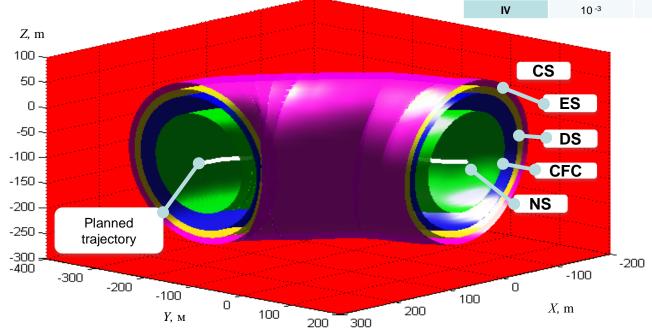


#### Estimation of flight situation boundaries

$$Z = \Phi^{-1} \left( P - \frac{1}{2} \right) \sigma + ZNS \qquad \text{where} \quad P = \begin{bmatrix} P_{CFC} \\ P_{DS} \\ P_{ES} \\ PCS \end{bmatrix}, \qquad Z = \begin{bmatrix} Z_{CFC} \\ Z_{DS} \\ Z_{ES} \\ ZCS \end{bmatrix}, \qquad \sigma = \frac{x - ZNS}{\Phi^{-1} \left( PCS - \frac{1}{2} \right)}$$

#### Visualization of flight situations in 3D space





Range safety criteria for unmanned air vehicles – rationale and methodology supplement. Supplement to document 323-99 / Range Safety Group, Range Commanders Council. – 1999. –75 p.

#### Estimation of a posteriori probabilities of flight situations

Conditional probability density function of multiparametric normal distribution

$$\rho_k(x) = \frac{1}{(2\pi)^{K/2} |B|^{-1/2}} exp \left[ -\frac{1}{2} \left( B^{-1} (x - M)^T \times (x - M) \right) \right]$$

 $x = (x_1, x_2, ..., x_s)$  – vector of parameters measurements,  $M = (\mu_1, \mu_2, ..., \mu_s)$  – vector of mathematical expectations for

each parameter *B* – matrix of MSD

 $s = \overline{1, K}$  index of corresponding parameter,

 $k = \overline{1, N}$  – index of corresponding class.

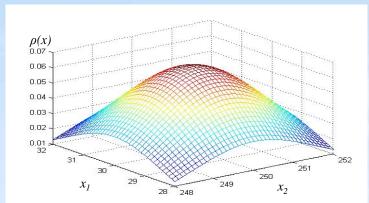
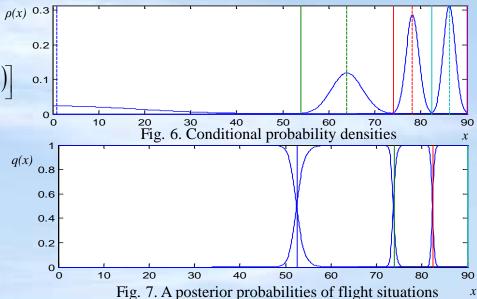


Fig.5. Density function of multi-parametric normal distribution



A posteriori probabilities of flight situations are defined

$$q_k(x_s) = \frac{\text{as:}}{\sum_{k=0}^{N} p_k \rho_k(x_s)}$$

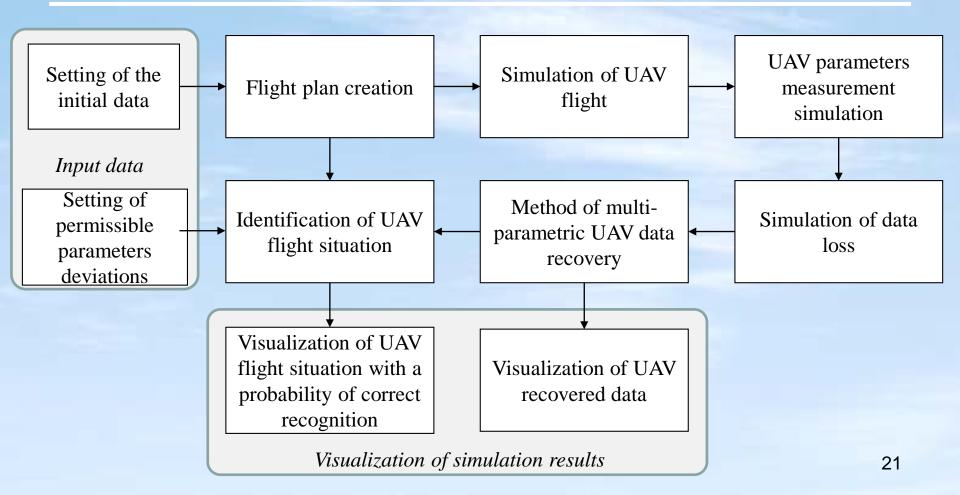
where  $p_k$  – a priori probabilities of flight situations

Criterion of recognition:  

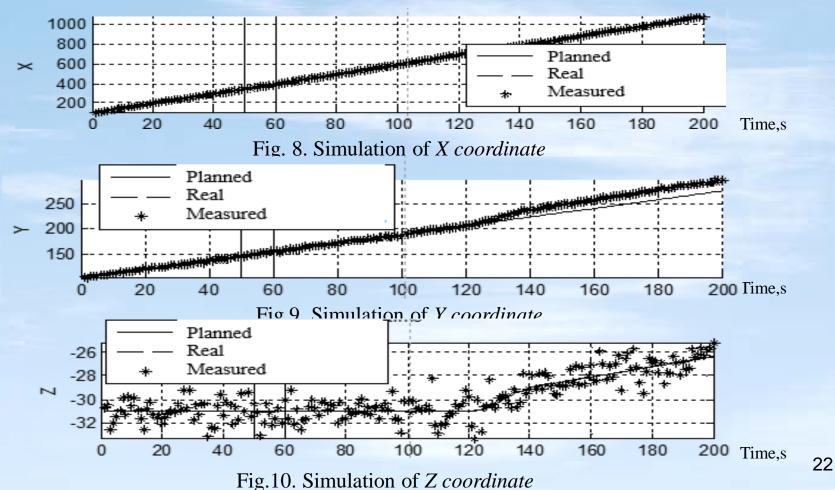
$$q_{\nu}(x_{\nu}) = max(q(x_{\nu}))$$

20

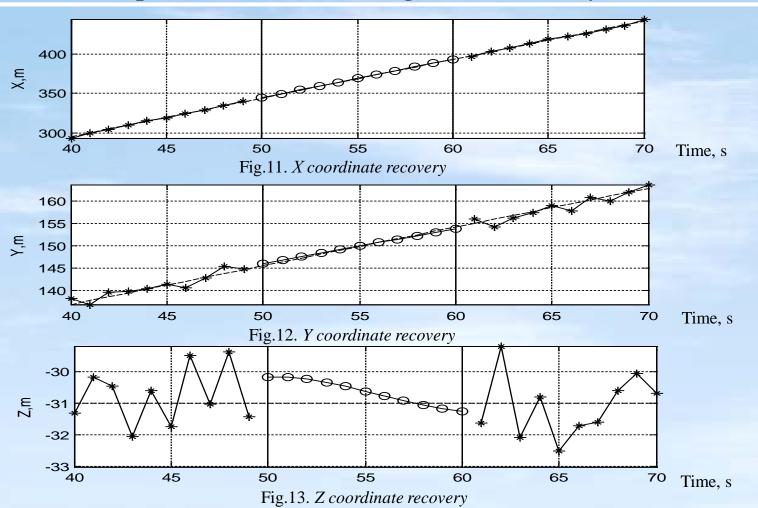
#### Verification by means of computer simulation



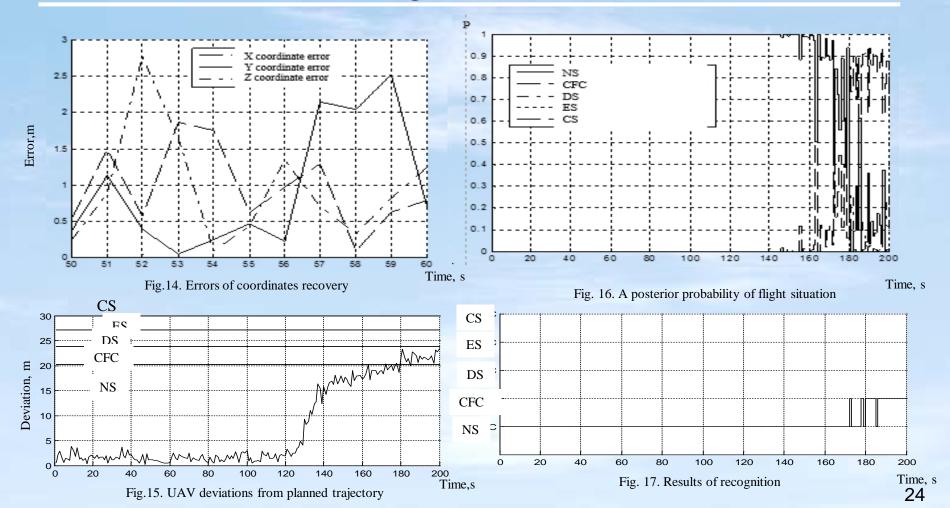
### Representation of UAV flight parameters simulation



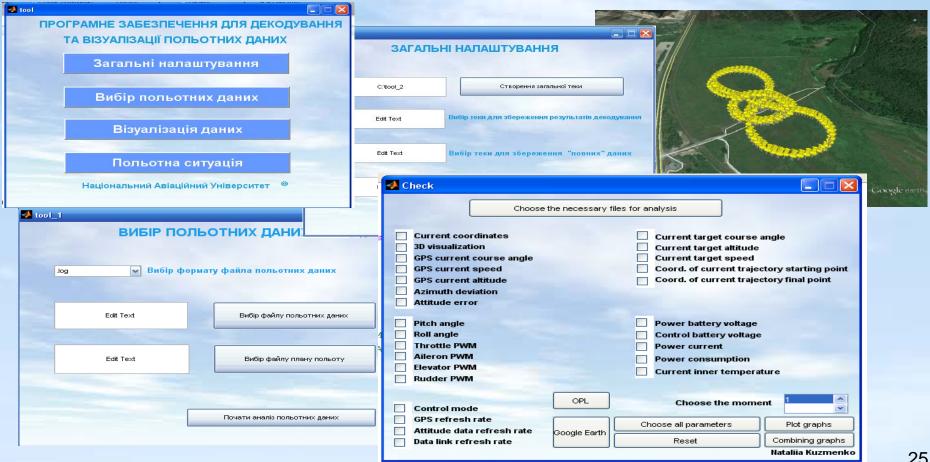
### Representation of UAV flight data recovery



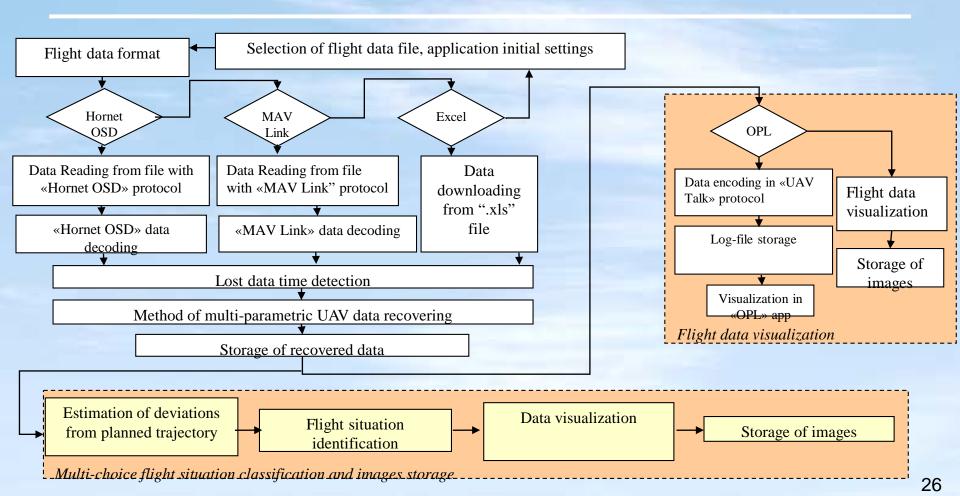
#### Simulation results of UAV flight situations multi-choice classification



#### Application for UAV flight data decoding and visualization



#### Application for UAV flight data decoding and visualization



#### Methods verification through experimental tests

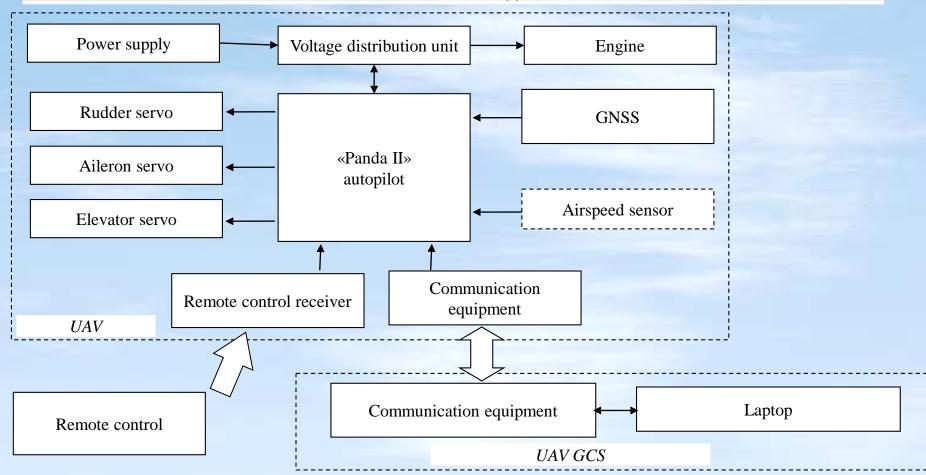
The venue is Khodosivka landfill (latitude 50.27° N, longitude 30.53° E).

UAV - "Cessna N877S", completed with on-board "Panda-II" equipment.

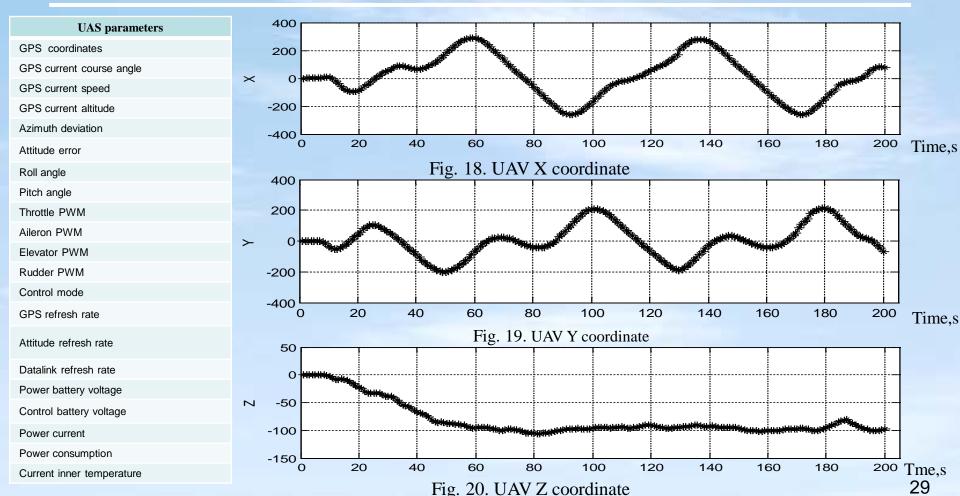


Flight data was transmitted over the radio channel to the GS and processed in specialized software

### **UAS block-diagram**



#### **Results of experimental tests**

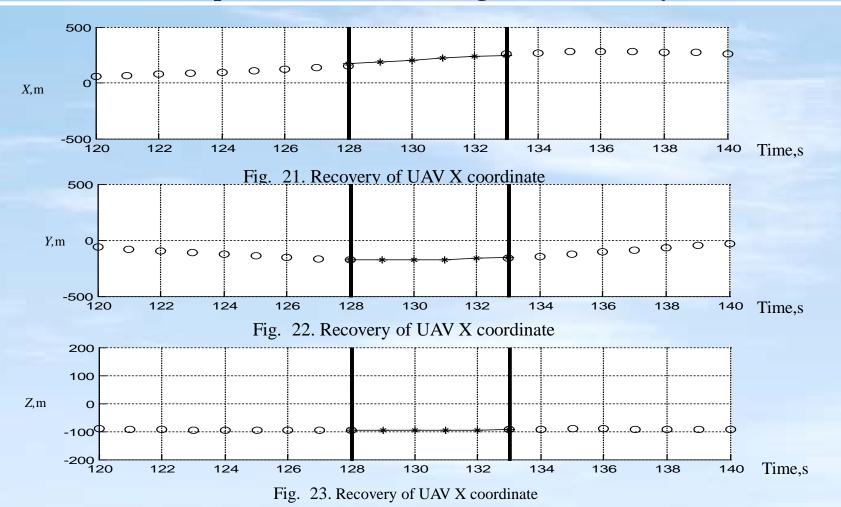


## **Results of experimental tests**

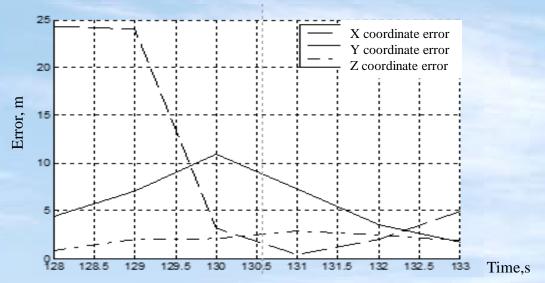
#### **UAV** trajectory

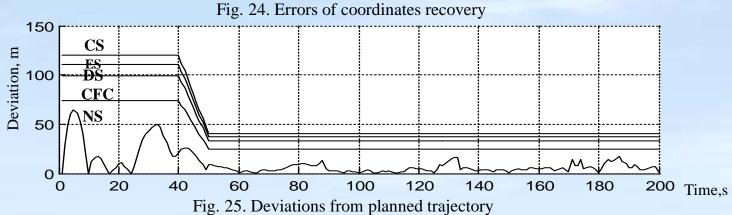


#### Representation of UAV flight data recovery

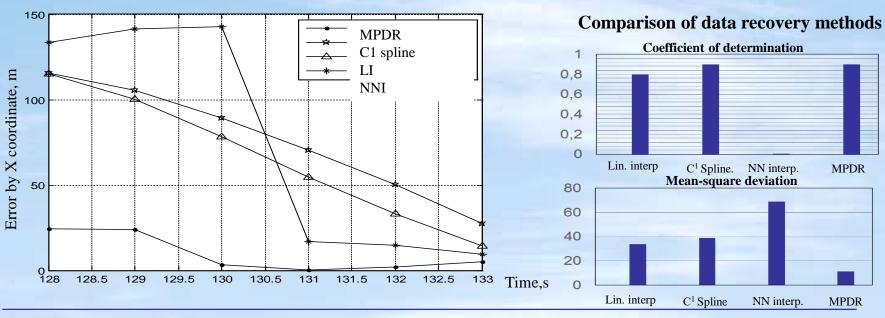


#### Representation of multi-choice classification of UAV flight situations



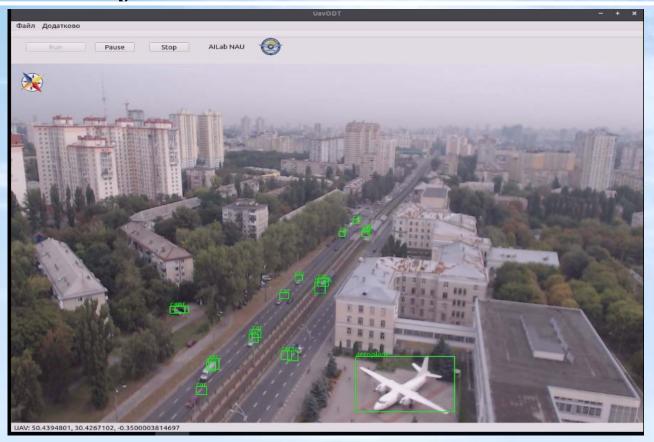


#### Comparison of X coordinate recovery by different methods



Recovery method	MSD, m	ME, m	Maximum error, m	Minimum error, m	Coefficient of determination
Linear interpolation	33,7	76,5	115,6	22,3	0,8
C¹ spline interpolation	39,0	65,9	114,9	14,4	0,9
Nearest neighbor interpolation	68,8	76,4	142,9	9,4	0,002
MPDR	11,2	9,8	24,3	0,4	0,9

# Object detection and classification

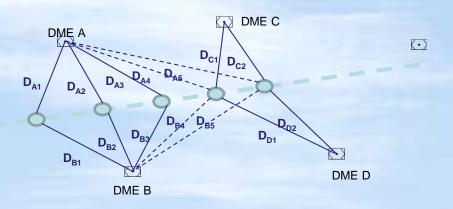


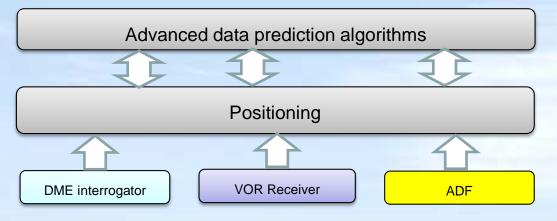
## **Alternative Positioning, Navigation, and Timing**

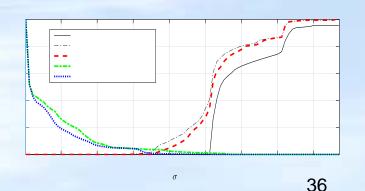
- Performance improvement of positioning by multiple Navigational aids (DME/DMEs, VOR/DMEs, VOR/VORs) by integration advanced methods of sensor data prediction and filtering
- Passive methods of positioning by multiple signals in space
- Location detection by Airborne Collision and Avoidance System data
- Vision based navigation system with image processing algorithms and its integration with GNSS and Inertial reference system
- Implementation of low-cost sensors in advanced data processing to ensuring safety and security levels and the desired performance gains in terms of resilience and cost efficiency
- An airspace performance analysis using advanced methods

# APNT. Performance improvement of positioning by multiple Navigational aids

Performance improvement of positioning by multiple Navigational aids (DME/DMEs, VOR/DMEs, VOR/VORs) by integration advanced methods of sensor data prediction and filtering







APNT. Passive methods of positioning by multiple signals in space

#### Passive positioning by data from

- Distance Measuring Equipment
- Automatic Dependent Surveillance Broadcast
- VOR



Fig. Receiving available signals in space by SDR

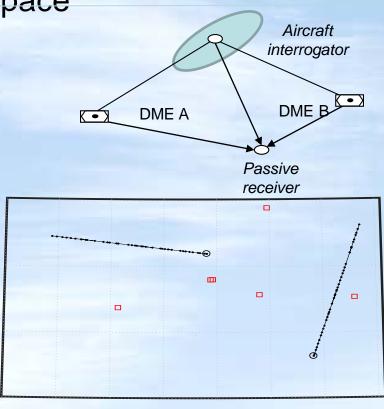


Fig. Ground tracks of "5082EF" and "4BBC81"

## APNT. Positioning by ACAS X data

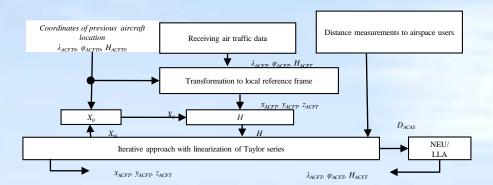
#### **ACAS X variants**

ACAS  $X_A$  – The general purpose ACAS X that makes active interrogations to detect intruders. ACAS  $X_A$  is the baseline system, the successor to TCAS II. The Standards are expected to be ready by 2018 and ACAS X may become operational in 2020.

ACAS  $X_O$  – ACAS XO is an extension to ACAS  $X_A$  designed for particular operations, like closely spaced parallel approaches, for which ACAS  $X_A$  is less suitable because it might generate a large number of nuisance alerts. The MOPS are jointly with ACAS  $X_A$  MOPS and also are expected to be ready by 2018.

ACAS  $X_U$  – Designed for Remotely Piloted Aircraft Systems (RPAS), incorporating horizontal resolution manoeuvres. Work on Standards has started in 2016 and is expected to be finished in 2020.

ACAS  $X_P$  – A future version of ACAS X that relies solely on passive Automatic Dependent Surveillance Broadcast (ADS-B) to track intruders and does not make active interrogations. It is intended for general aviation aircraft (that are not currently required to fit TCAS II).





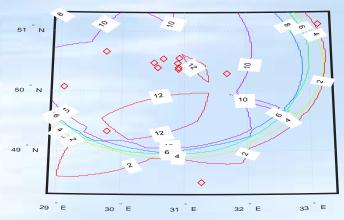
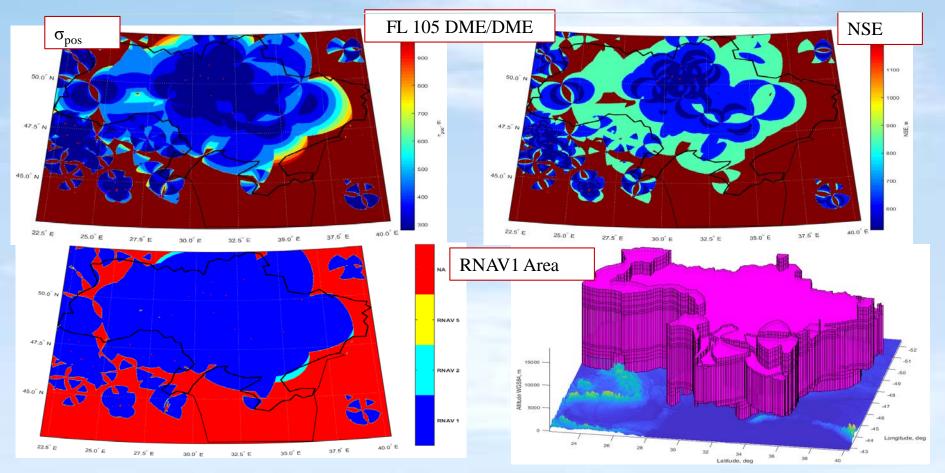
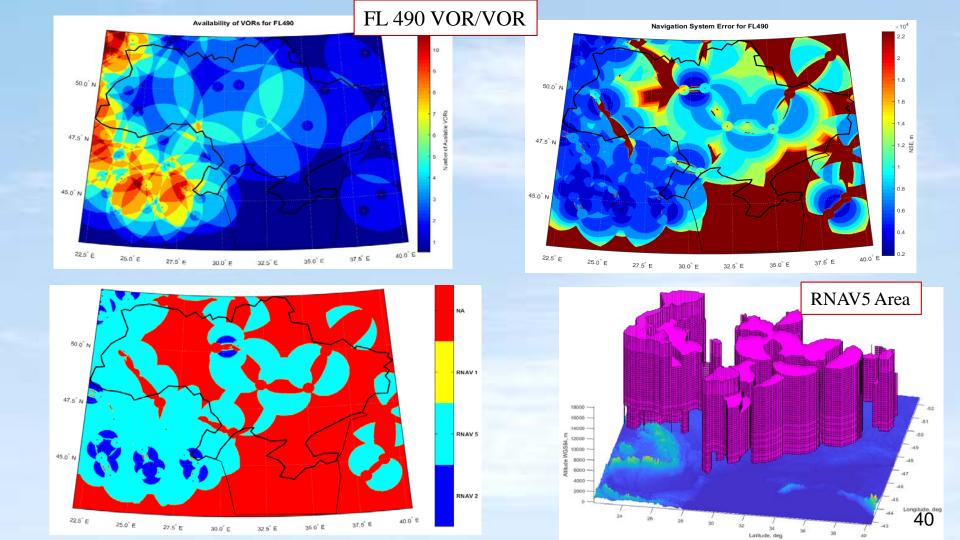
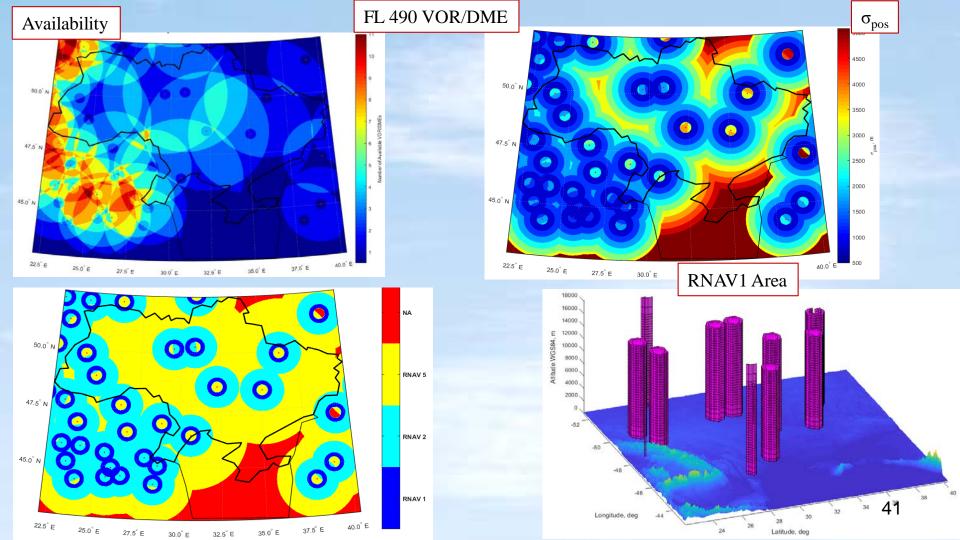


Fig. Availability of ADS-B data for positioning

## An airspace performance analysis using advanced methods









World Congress "AVIATION IN THE XXI-st CENTURY"

# The 9th World Congress "AVIATION IN THE XXI-st CENTURY"

National Aviation University, Kyiv,
Ukraine
October, 2020

# Thank you for attention!