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Article

The concept of networked distributed engine control system of future air vehicles

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Abstract: This report is considered different aspects of the concept of the networked distributed engine control system (DECS) of future air vehicles. These aspects include the following: the structure of multiple networks similar to NATO Generic Vehicle Architecture (NGVA), the role of Artificial Intelligence (AI) in DECS, and the use Augmented Reality (AR) as Human-Machine Interface between AI and pilots. Deployment of AI solutions for monitoring equipment in on-board infrastructure can be provided on physical or virtual servers and in the clouds. In this case, it is possible to use various methods of alerting the pilot and ground personnel on the basis of AR. The use of AI allows covering an unlimited set of scenarios, to provide an assessment of the likelihood of equipment failure, classification alarm is normal, and recognition of the development of defects. To collect Big Data from sensors and the pre-processing of this data before a machine learning (ML) procedure it is proposed to form data sets with the help of the face-splitting matrix product. To decrease the time of reaction of Neural Networks it has been suggested the implementation of advanced tensor-matrix theory on the basis of penetrating face product of matrices. Other important results of the report are a possible version of the AR data format for DECS and a proposal about the use of non-orthogonal frequency discrete multiplexing (N-OFDM) signals to data transfer via fibre optics.

Keywords: distributed engine control system (DECS), NGVA, Data Distribution Service (DDS), Artificial Intelligence (AI), Augmented Reality (AR)

1. Introduction

The distributed engine control system (DECS) of future air vehicle should be built on the base of networking principle as the part of an integrated, hierarchical, multidimensional and multiple networks system on the air vehicle board. The paper reviews few aspects that contribute to the DECS concepts: the DECS architecture, the roles of Artificial Intelligence (AI) and Augmented Reality (AR).

2. General view of the DECS architecture

As the prototype of the DECS architecture the NATO Generic Vehicle architecture (NGVA, STANAG 4754) (Figure 1), which is used in combat vehicles, can be used, and the similar approach - in the GVA Standard of UK or VICTORY Architecture of combat vehicles in USA. Standard for the general structure of NGVA vehicles [1-3] provides a networked principle of systems management using data transmission gateways and control commands). However, the expansion of the range of on-board systems and their functions leads to the need to transform NGVA into a multi-network environment. DECS should combine the multiple networks such as a control network, a diagnostic and maintenance network to transfer the sensor data and 10-bit video streams [4] from different high resolution cameras in the space around of engines (similar to SpaceX Starship prototypes SN8 – SN11 etc.). On the other hand, DECS should have a full integration with firefighting network because it uses the same sensors and control object.

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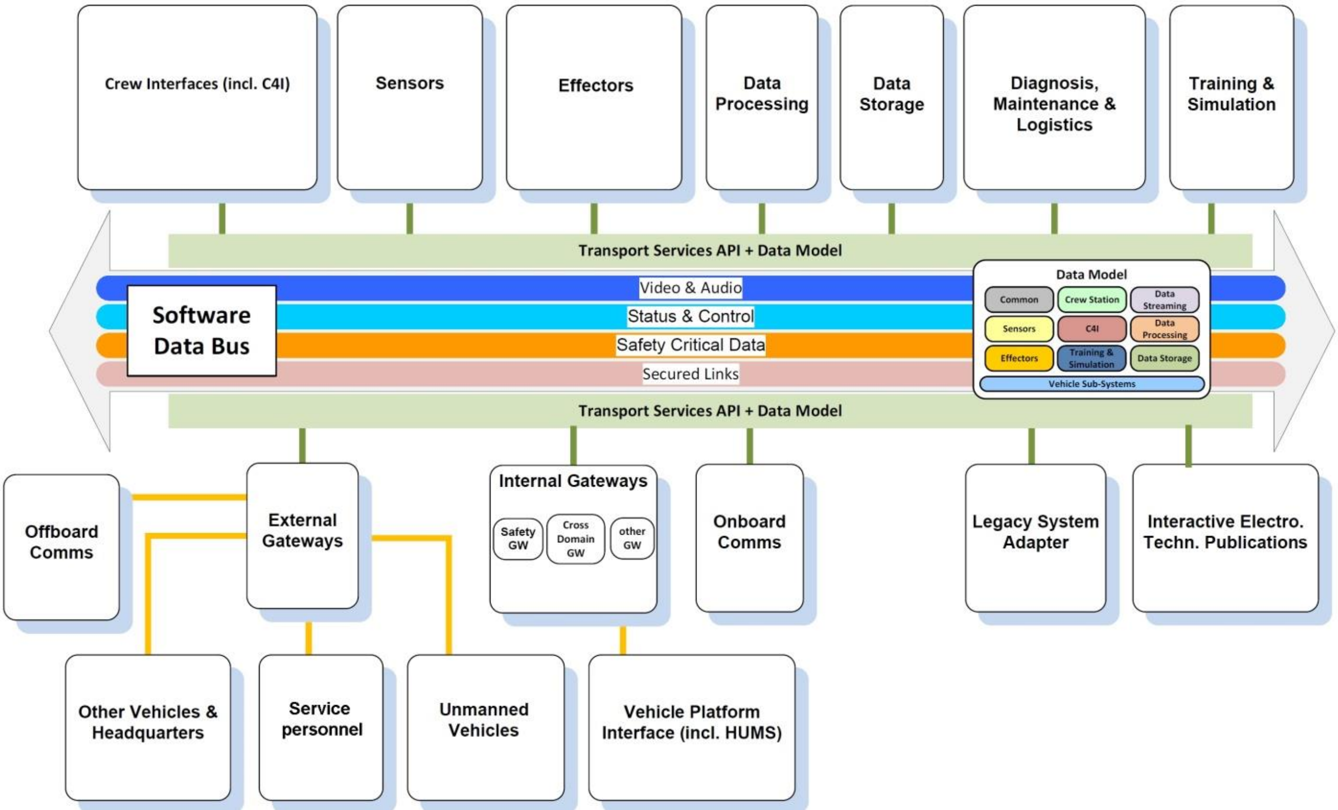

Figure 1. NGVA Data Infrastructure Context - adapted for DECS from [2].

In this regard for the transfer of control and feedback data inside the DECS, the current trend is the use of real-time Data Distribution Service (DDS) over a wireless IP (Internet Protocol) network (also used in NGVA) based on ROS-2 (Robotic Operating System) or a similar version of ROS-M. As the dissemination protocol of data can also use combination of DDS with MQTT-SN, which is a publish/subscribe messaging transport that was designed for vehicle-to-vehicle telemetry, sensors networks, and Internet-of-Things (IoT). It is very relevant to DECS because this network will be similar to IoT.

To reduce the jitter and the latency of engine control networks, the integration of DDS with Time-Sensitive Networking (DDS-TSN), which will have the jitter on a level not more as few microseconds, can be used. The concept of integrating NGVA with Land defensive aid suite (DAS) architecture [5, 6] or the Helicopter Integrated Defensive Aids System (HIDAS) can be taken as an example of the transformation NGVA into a multi-network environment (Figure 2). This combined architecture of multiple networks transforms a collection of controllers, switches, sensors, and protective equipment such as effectors, actuators, into a comprehensive defensive suite system. All these devices should have a common address space with support of few applications in multiple networks similar to MIPS.

To protect against Electromagnetic Pulse (EMP) threats and to build fault-tolerant ruggedized engine control networks with high temperature-compatible communications, fibre-optic engine control networks should be used. In this context, the best solution will be the use of several Sensor Open Systems Architecture (SOSA) single board computer units and SOSA Input-Output modules with the fibre-optic connectors to sensors. Such connectors have a maximum data transfer speed 22 Gbps and all SOSA units are fully ruggedized. It worth to noting, that the SOSA standard is shared only for USA at present but it will be expanded to other countries in the future.

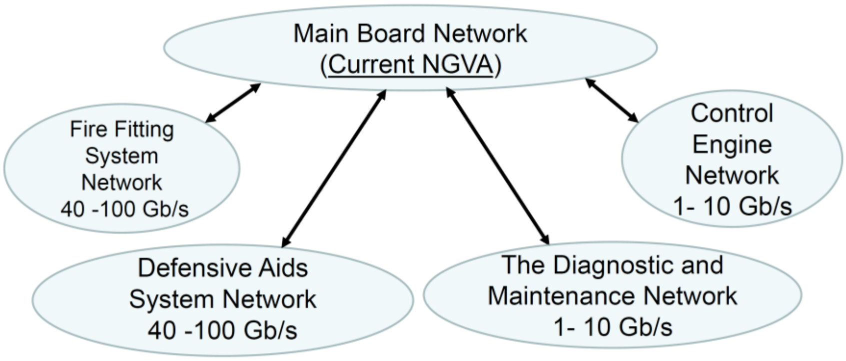

Figure 2. Concept of NGVA as Network of Networks (Multi-Network)

Each network inside a DECS (control network, diagnostic and maintenance network, firefighting network) need to have one or several distributed SOSA single board controllers with gateway between such networks inside the DECS, and the gateway to other networks of an air vehicle beyond DECS. For its better compatibility, the networks on board an air vehicle need to expand general principles of building of DECS (common DDS-TSN Data model etc.) to a hierarchy of such networks.

In the future, the fibre-optic engine control networks can be combined with wireless access on the basis of THz waves.

3. Hyperspectral cameras and Infrared Imaging Video Bolometers

The faults identification and decision-making process regarding the current state of the DECS can be grounded on the measurement of the total radiated power from the plasma jet of the engine. Total radiation and the spatiotemporal radiation profiles at the outlet of the combustion chamber can be estimated by the various types of bolometer diagnostic methods on different devices, such as hyperspectral cameras with 10-bit color video, the Infrared Imaging Video Bolometers (IRVB) etc. The crucial parameters for the efficient fault identification are possible to obtain on from an overall power balance measurement and spectral estimation, which approximately indicates the total impurity content of the plasma. In the general case, bolometers detect radiated power from the plasma jet over a wide spectral range, starting from soft X-Rays and extending to the infrared band.

Artificial Intelligence (AI) has to be used for the image classification of the area localization of the defect, and the semantic pixel-level segmentation of the images data sets from such video streams

4. The role of Artificial Intelligence in DECS

4.1. General Remarcs

Since Artificial Intelligence (AI) is the basis of the future control networks [7], the implementation of AI is an important trend in the development of the future DECS. NATO experts use two alternative definitions of artificial intelligence [8]:

Definition 1: "AI is the capability that is provided by algorithms of selecting optimal or sub-optimal choices from a wide possibility space, in order to achieve goals by applying strategies which can include learning or adapting to the environment".

Definition 2: "Artificial intelligence (AI) refers to systems, that are designed by humans, which given a complex goal, act in the physical or digital world by perceiving their environment, interpreting the collected structured or unstructured data, reasoning on the knowledge derived from this data and deciding the best action(s) to take (according to pre-defined parameters) to achieve the given goal. AI systems can also be designed to learn to adapt their behavior by analyzing how the environment is affected by their previous actions".

In the context of the DECS, definition 2 is recommended here [7]. AI is useful in particular with respect to making heterogeneous control systems work together; to improve data exchange; to working with fewer resources of data; to making coordination of sensors, actuators, and controllers onboard air vehicles, threat detection and identification [7]. AI can also perform the following functions inside DECS: warn about the possibility of a critical situation, determine a safe mode of an engine operation, detect suddenly emerging threats that impede engine functionality, visually warn for marking areas requiring special attention, the analysis of hyperspectral images of the local zones of the engine to identify changes in its surface, which is a sign of possible damage, identification against the backdrop of natural wear. AI is a means of improving timeliness (fast threat, pop up, numerous threats), derivation of intents, situational awareness and evaluation [7].

As an example of such an approach, the AI/ML recognition of a defect evolving in a fuel pump can be considered. The data from pump rotation speed (rpm), oil temperature, bearings temperature, bearings vibration (mm/sec), rotor displacement (mm), etc. sensors can be used as AI training database. It is possible to obtain up to 50 - 100 values of parameters per second from one control object from these sensors. On the other hand, the fault type that was registered by repair teams or by diagnostic equipment on the failures and identification of defects must be used for supervised learning. A neural network has to provide real-time monitoring of the development of faults in pumps on the basis of the flow of process parameters and reports of repair personnel about detected defects. It is possible to predict the appearance of defects of this type 48 hours before their appearance.

AI provides a process of detecting inconsistencies in the behavior of engine systems, an identification of anomalies, and their classification in real time, and analysis of the root cause of the symptom. Using AI in clustering inconsistencies detects outliers in basic and general characteristics and to ensure information security.

4.2. Embedded Machine Learning for Predictive Maintenance

Predicting the time of occurrence of an engine defect is possible by analyzing data from sensors using AI. In particular, AI can be applied to detect corrosion, cracks, fluid leaks, contamination from oil and fuel drips (via cameras), and identification of defects by acoustic noise and vibration. Intelligence Situational Awareness Analyzer as a smart component allows sensory processing to evolve without affecting sensor nodes or response control.

To collect Big Data from sensors and preprocessing these data before Machine Learning (ML) procedure, it is proposed to form data sets with the help of the face-splitting matrix product [9, 10]. The 1st stage of such processing is the building of incidence matrices for every engine mode or for every partial network inside the structure of DECS.

Assume that there are 3 sensors that are indicating their parameters in the original set of four ranges (a sub-normal, a normal, an over-normal, and a critical level). For simplicity, consider three sequential modes of engine operation or three different networks inside the DECS.

Compose a so-called incidence matrix [11] for each of the sequential modes of the engine. Its rows will correspond to a specific sensor, and its columns will correspond to the parameters range. In this case, the one in each line corresponds to the parameter range that was received from the sensor, while for all other ranges there will be zeros. In the general case, the number of columns has to be equal to the maximum number of ranges in the considered data set. In the above context, the maximum number of ranges is equal to four. Before proceeding to the incidence matrices, consider the results of successive measurements (Table 1).

Table 1. Results of successive measurements

Number of sensor	Sub-normal level	Normal level	Over-normal level	Critical level
X-Mode (X-Network)				

Sensor 1	0	1	0	0
Sensor 2	1	0	0	0
Sensor 3	1	0	0	0
		Y-Mode (Y-Network)		
Sensor 1	1	0	0	0
Sensor 2	0	1	0	0
Sensor 3	0	0	0	1
		Z-Mode (Z-Network)		
Sensor 1	0	0	1	0
Sensor 2	0	0	0	1
Sensor 3	0	1	0	0

Hence, we obtain incidence matrices of the form:

$$X=\begin{bmatrix}0&1&0&0\\1&0&0&0\\1&0&0&0\end{bmatrix};Y=\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&0&1\end{bmatrix};\ Z=\begin{bmatrix}0&0&1&0\\0&0&0&1\\0&1&0&0\end{bmatrix} \tag{1}$$

The 2nd stage of preprocessing of data set is the computing of higher order tuple co-occurrences matrices using the face-splitting product of incidence matrices. Moving on to the problem of analyzing combinations of sensor readings in a sequence of modes, as indicated in [11], it is necessary to use the face-splitting product of the matrices for this. In particular, the co-occurrence matrix for the analysis of triple combinations can be formed on the basis of the 1st incidence matrix and its version in the form of the face-splitting product (symbol □ [9, 10]):

$$C=X^T(Y\,\square\,Z)=\begin{bmatrix}0&1&0&0\\1&0&0&0\\1&0&0&0\end{bmatrix}^T\left[\begin{array}{cccc:cccc:cccc:cccc}0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0\\0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0\\0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0\end{array}\right]=$$

$$=\left[\begin{array}{cccc:cccc:cccc:cccc}0&0&0&0&0&0&0&1&0&0&0&0&0&1&0&0\\0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0\\0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\end{array}\right]. \tag{2}$$

The resulting matrix has a dimension of 16 × 4 and can be represented in the form of 4 blocks, each of which corresponds to the one of the parameter ranges (see Table 2).

Table 2. The pattern of sensors states

	Y_1= sub-normal level				Y_2= normal level				Y_3= over-normal level				Y_4= critical level			
	Z_1	Z_2	Z_3	Z_4	Z_1	Z_2	Z_3	Z_4	Z_1	Z_2	Z_3	Z_4	Z_1	Z_2	Z_3	Z_4
X_1	0	0	0	0	0	0	0	**1**	0	0	0	0	0	**1**	0	0
X_2	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0
X_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The numbers in the role of elements of the matrix C characterize the frequency of occurrence of specific triplets of parameter ranges in the studied sequence of modes, taking into an account their order in the sequence. For example, from the first block of the matrix, it follows that the sets of working parameter ranges ($X_2Y_1Z_3$), ($X_1Y_2Z_4$), and ($X_1Y_4Z_2$) occur once. Other combinations of parameter ranges were not observed. Actually, Table 2 reflects the pattern of states of sensors. Such approach can be expanded to more sensors and modes of engine work or partial networks inside DECS. Furthermore as an object of pairwise co-occurrences, the digital twins of engines (DECS) can be used.

4.3. Digital twins

Digital twins Technology [12, 13] will have a very important role for Predictive Maintenance of an engine system. A digital twin is a software analogue of a physical 3D device which simulates internal processes, technical characteristics and behavior of a real object under the influence of the interferences and the environment [12, 13]. An important feature of the digital twin is the use of information from the sensors of a real device which operates in parallel to set input influences on it. The use is possible both online and offline. Further, it is possible to compare the information of the virtual sensors of the digital twin with the sensors of the real device to identify anomalies and the reasons for their occurrence. A digital twin can be used on board air vehicles and/or on the cloud of command post (air base).

4.4. Advanced approach to description of Neural Network model

To decrease the reaction time of Neural Networks, the implementation of advanced tensor-matrix theory on the basis of penetrating face product of matrices is suggested. According to the definition [10] the penetrating face product of the $p \times g$ matrix **A** and n-dimensional matrix **B**=[B_n] ($n > 1$) which is unfolded in the block of rows or block of columns with $p \times g$ blocks is a matrix of the form:

$$A \blacksquare B = [A \circ B_r], \tag{3}$$

where $A \circ B_r$ is the elementwise (Hadamard) product of matrices [14], ◙ is the symbol of the penetrating face product.

If **B** is block-row matrix then Eqn (4) applies:

$$A \blacksquare B = [A \circ B_r] = [A \circ B_1 \mid A \circ B_2 \mid \ldots \mid A \circ B_r \mid \ldots]. \tag{4}$$

Few properties of penetrating face product of matrices are:

$$\mathbf{A} \blacksquare \mathbf{B} = \mathbf{B} \blacksquare \mathbf{A}, \tag{5}$$

$$A \square A = A \blacksquare (A \otimes 1^T), \tag{6}$$

where □ denotes the face-splitting product of matrices, ⊗ is the symbol of Kronneker product, $\mathbf{1}^T$ – vector-row of ones. If c is a vector then c □ **A**= **A** □ c=c ◙ **A**= **A** ◙ c.

An example:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{bmatrix}, \; B = \left[\begin{array}{cc:cc:cc} b_{111} & b_{121} & b_{112} & b_{122} & b_{113} & b_{123} \\ b_{211} & b_{221} & b_{212} & b_{222} & b_{213} & b_{223} \\ b_{311} & b_{321} & b_{312} & b_{322} & b_{313} & b_{323} \end{array}\right],$$

$$\mathbf{A} \blacksquare \mathbf{B} = \left[\begin{array}{cc:cc:cc} a_{11} \cdot b_{111} & a_{12} \cdot b_{121} & a_{11} \cdot b_{112} & a_{12} \cdot b_{122} & a_{11} \cdot b_{113} & a_{12} \cdot b_{123} \\ a_{21} \cdot b_{211} & a_{22} \cdot b_{221} & a_{21} \cdot b_{212} & a_{22} \cdot b_{222} & a_{21} \cdot b_{213} & a_{22} \cdot b_{223} \\ a_{31} \cdot b_{311} & a_{32} \cdot b_{321} & a_{31} \cdot b_{312} & a_{32} \cdot b_{322} & a_{31} \cdot b_{313} & a_{32} \cdot b_{323} \end{array}\right].$$

This example can have the following interpretation. The matrix A can be considered as an input matrix of picture pixels. In this case, every block of matrix **B** corresponds to a block of weight coefficients for few neurons in one layer of the Neural Network. Further steps of data processing in the considered neural network can be different depending on the structure and type of layers. If we have a convolutional neural network, then the matrix A ◙ B must be multiplied by a vector of ones. In particular, the multiplication can have one of the following forms:

- A vector-row 1^T(A ◙ B);
- A vector (A ◙ B)×**1**, where × is the conventional product of matrices, **1** – a vector of ones;
- A matrix (**A** ◙ **B**) [×]**1**, where [×] is the blocked conventional product of matrices, **1** – a block vector of ones;
- a scalar $\mathbf{1}^T$(**A** ◙ **B**)**1.**

Results of such multiplication will be used as argument of an activation function, as an example:

$$\mathbf{Softmax((A \circledcirc B)\times 1+d)} \text{ or } \mathbf{ReLU(1^T(A \circledcirc B)1+d)}, \tag{7}$$

where **d** is a vector or a scalar,

$$\mathbf{Softmax((A \circledcirc B)[\times]1+d)} \text{ or } \mathbf{Tanh(1^T(A \circledcirc B)+d)}, \tag{8}$$

where **1** is a block vector of ones.

As an option for implementing the penetrating face product of matrices in the TensorFlow machine learning library, we can consider the task of element-wise multiplication of a matrix by a vector based on the properties of broadcast transmission. The tf.multiply operator which is built into TensorFlow can be used (Figure 3; [15]) for this task. However, this approach does not work in relation to matrices and requires preliminary vectorization of a matrix of lower dimension in combination with vectorization of blocks of a block matrix which is consistent with it. The block vectorization procedure, which is necessary for this task, is described in Figure 3 [15].

```
In [55]: M.eval()
Out[55]:
array([[1, 2, 3, 4],
       [2, 3, 4, 5],
       [3, 4, 5, 6]], dtype=int32)

In [56]: V.eval()
Out[56]: array([10, 20, 30], dtype=int32)

In [57]: tf.multiply(M, V[:,tf.newaxis]).eval()
Out[57]:
array([[ 10,  20,  30,  40],
       [ 40,  60,  80, 100],
       [ 90, 120, 150, 180]], dtype=int32)

In [58]: tf.multiply(V[:, tf.newaxis], M).eval()
Out[58]:
array([[ 10,  20,  30,  40],
       [ 40,  60,  80, 100],
       [ 90, 120, 150, 180]], dtype=int32)
```

Figure 3. Execution of the penetrating face product of the vector and matrix using the TensorFlow library [15].

When solving the problems of improving special AI software, it is necessary to take into an account the hardware aspects of its implementation. Therefore, the requirement to make a time scale of data processing in peripheral devices (Edge Computing) close to real becomes an essential. This trend is driven by the need to migrate cloud AI technologies to endpoints.

Therefore, in the interests of data processing in multilevel hierarchies of neural network clusters, one should take into an account the multicore architecture of microprocessor-based tools for implementing a special software when performing block face-splitting product operations [10] and generalized face-splitting products of matrices [16]. It is also relevant for specialized tensor-matrix computers, the development of technologies of which has intensified in the last few years. All these factors taken together will simplify the hardware implementation of special software for AI systems and provide a noticeable increase in their performance.

5. Augmented Reality (AR) technologies for DECS

5.1. AR Data

The communication bridge and feedback mechanism from AI to a Human for the support of decisions making should use Augmented Reality (AR) technologies. The cloud or multi-network cooperative AI algorithms can be used for this task. These algorithms are distributed between several networks and systems of air vehicle DECS and they can create combined three-dimensional outlines AR visions for the common situation awareness picture.

In regards to the above, the interoperability has to be provided between the format (model) of data that is generated at an engine networks and the software of AR symbols playback devices, which must identify the type of data, and send it to the display (visual data), speakers (acoustic symbols) or tactile elements (gloves, belts, etc.). In some cases, engine data can be transformed into AR data (and back) in the DECS. But in most general case, there is a need to exchange AR-specific data or AR data blocks, because not all AR data is the engine feedback information. For an example of such a context is AR 3D virtual models of engine for testing engine systems before mission, anime, avatars, shell symbols of sensors or actuators, which was recognized by AI on the point cloud and video streams, also some elements of synthetic environment, etc. In some cases, for cross-networks exchange of AR information it will be sufficient to use the selection of symbols from a common AR database onboard air vehicle by using only position number of AR symbols in such database (catalog) with additional geographical localization. All these tasks can be decided by standardization of an AR data transfer protocol (structure and size of a typical data block). A possible AR data format is depicted on Table 3.

Table 3. Possible structure of AR data block in cross-networks domain.

AR Marker (1 bit)	Modification of AR data (1 bit)	UID-transmitter (16-32 bits)	UID-receiver (16-32 bits)	Category of AR (2 bits)	
0 – AR data; 1 – other data	0 – it is 1st modification of AR	Identification of AR source	Identification of correspondent	Visual or Acoustic or Haptic	
Type of Visual AR (1 bit)	**Coordinates of symbols (32 bits)**	**Type of AR Symbol (12 bits)**	**Colour of AR Symbol (8 bits)**	**Block of text for display (256 bits)**	**Hash (32 bits)**
Annotation or Simulation	Location and accuracy of AR object	Selection of symbols from data base or syntheses by AI	256 colours	Comments for symbols (annotation)	

Also, for the transfer of AR data blocks, one can use the Variable Message Format (VMF) (STANAG 5519 is under development). On the other hand, cross-networks transparent AR data traffic needs to be transmitted by using cyber and jamming protected communication. In the future, blockchain technology can be used, but the big issue today is limited by performance of on board communication links. In this context; current data transfer standards via fibre-optics have to be updated on the base of new waveforms and technologies.

5.2. The non-orthogonal frequency discrete multiplexing (N-OFDM) of signals

For the data transfer via fibre-optics, the idea of spreading spectrum with non-orthogonal frequency discrete multiplexing (N-OFDM) of signals is relevant. It can increase data performance by better spectral efficiency (Figure 4).

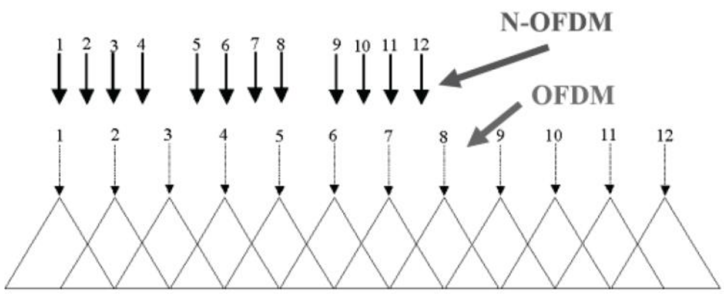

Figure 4. The arrangement of N-OFDM (OFDM) signal.

Taking into an account that the coding of N-OFDM signals is accompanied by amplitude-phase modulation of the carrier frequencies, the estimates of quadrature components of signals in the receiver can be obtained from the voltages of frequency filters synthesized by the fast Fourier transform (FFT). In particular, the response voltages U_j of the frequency filter without taking noise into account give a system of equations [17] can be written as:

$$U_j = \sum_{\mathrm{m=1}}^{\mathrm{M}} a_m f_j(\omega_m), \tag{9}$$

where $f_j(\omega_m) = \dfrac{\sin\left(S\left[j\dfrac{\pi}{S} - \omega_m\right]\right)}{\sin\left(j\dfrac{\pi}{S} - \omega_m\right)}$, j=1, 2, …, M, is the value of the amplitude-frequency response (AFR) of the frequency filter number "j" synthesized by means of FFT; and ωm is known carrier frequency among the totality of the prescribed frequencies expressed in segments of the AFR main lobe width of the FFT filter, am – an amplitude of signals, M –quantity of signals, S is the dimensionality (number of points) of the FFT operation.

In the case of deterministic interpretation of the signal mixture in the absence of Doppler's shifts of frequency, the respective relationships have the form [17]:

$$a_m^{c(s)} = \frac{\det_m^{c(s)}}{S \times \det}, \tag{10}$$

where m=1,2,…, M; $\det_m^{c(s)}$ is a partial determinant obtained from the determinant

$$\det = \begin{vmatrix} f_1(\omega_1) & f_1(\omega_2) & \dots & f_1(\omega_M) \\ f_2(\omega_1) & f_2(\omega_2) & \dots & f_2(\omega_M) \\ \vdots & \vdots & \dots & \vdots \\ f_M(\omega_1) & f_M(\omega_2) & \dots & f_M(\omega_M) \end{vmatrix} \tag{11}$$

by replacing the respective column by the vector $\mathrm{B}^{\mathrm{c(s)}} = \begin{bmatrix} U_1^{c(s)} & U_2^{c(s)} & \dots & U_M^{c(s)} \end{bmatrix}$, where $U_m^{c(s)}$ are quadrature components of the complex response of the FFT-filter number *"m"*.

5.3. Other aspects of AR in the context of DECS

The scope of AR applications also includes visualization of data from embedded monitoring sensors on the engine of air vehicles to inform the pilot and nearest logistic site about current state of engine(s) on board of the air vehicle, fuel, health of engines systems. AR data can be used to control engine with the transmit video directly if it is needed in a degraded visual environment (fog, dust, smoke, aerosols).

On-board cross-networks sharing of AR data will radically update the learning and training process for crews on the frameworks of virtually missions. As noted by other

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researchers, AR data can be used as virtual combination of live and synthetic environment elements as well. In this context, AR devices can be used to display synthetic entities or events to live crew of air vehicles. The similar infrastructure can be considered as an example of a connection of engine of air vehicles with AR system to the logistic base architecture as well. The vehicle's on-board computer will be used as a cloud server of such AR data.

In the general case, a lot of datasets about dynamic objects status can be used as the information to build other AR annotations. A rotation (Figure 5) or vibration of symbols or the use of pulsation of symbols and other animation effects can be used as an example of the representation of dynamic state of object.

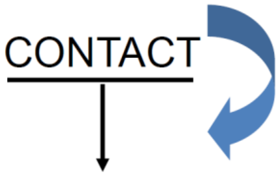

Figure 5. Example of Report AR Symbol with rotation effect.

6. Conclusions

The considered concept of DECS can be used as a base of the future standardization such systems. The current situation is that existing standards in the DECS area are not fully developed. Moreover, there is no overall and long-term plan for establishing a set of standards which are considering the aspects of interoperability. Some initiatives and technology trends which are believed to help on the current situation are under discussion.

The key factor to ensure the interoperability of DECS subsystems is to develop DECS standards as a System of Systems of Standards (S3) [18]. DECS S3 should represent interoperability, and it is defined in an integrated, hierarchical, multidimensional and multifunctional system of normative documents that form a system of its own. The need for such a structured DECS S3 is caused by the fact that it has to ensure development, testing and maintenance over the entire systems of systems' life cycle including all engines subsystems, and it should be reflected all by relationship between them.

The very important goals are a standardization of AR data format and AI data sets for ML. At a DECS level, the standardization can be applied advantageously in many other areas, for example:

- To standardize the sensor and effector interfaces, which allow the innovations in the nodes;
- To determine the composition of software components;
- to introduce the modularity to the controller level;
- to validate a DECS, etc.

All future DECS standards should remain open enough to accommodate new technologies.

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