Project Dissemination
Athens
24-11-2015

ACROSS

Advanced Cockpit for Reduction
Of Stress and Workload

Presented by
Aristeidis Nikologiannis

Prepared by
Aristeidis Nikologiannis
Security & Safety Systems Department
Hellenic Aerospace Industry S.A. (EAB)

Crew Health Monitoring Systems

A European Commission Seventh Framework Programme

This document is produced by the ACROSS consortium and the research leading to these results has received funding from the European Community's Seventh Framework programme (FP7/2012-2016) under grant agreement no ACP2-GA-2012-314501

EUROPEAN COMMISSION
European Research Area

General Information

- The ACROSS is an EC project aims to:
  - Develop new cockpit applications and human-machine interfaces, with the overall goal of reducing crew workload and supporting crew in dealing with difficult situations, thus enhancing flight safety and performance

- ACROSS stands for:

"Advanced Cockpit for Reduction of StreSs and workload".

  - The use of the adjective "advanced" reveals the innovative nature of the project and its fundamental aim to develop technologies that do not exist today rather than to improve the existing ones

- Across focuses on advancing:
  - cockpit systems regarding aviate, navigate, communicate and management systems
  - monitoring systems that evaluate the crew's status and performance during flight

Contents

- ACROSS Project Overview
  - Crew Health Monitoring System

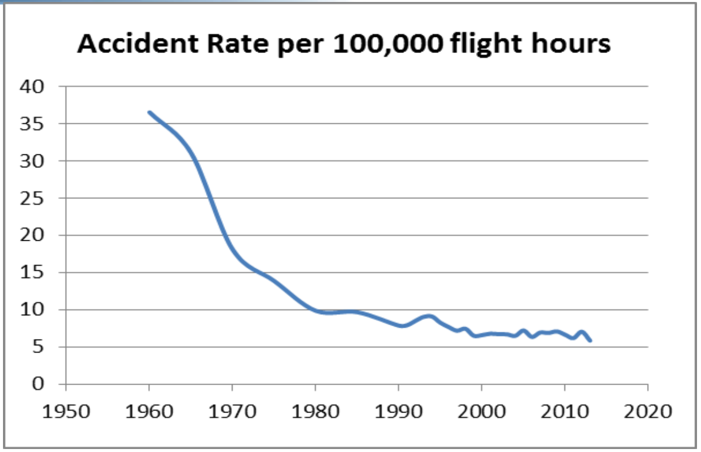
ACROSS Overview

Aristeidis Nikologiannis
Hellenic Aerospace Industry (HAI)

ACROSS Context

- Improve Flight Safety

- A large percentage of recent accidents can be linked to human factors
  - ✓ Crew has non-complete situational awareness
    - ✓ difficulties in perception of the environment
    - ✓ crew does not understand
      - what is happening
      - what the system does
      - what the consequences of an action
  - ✓ bad crew coordination with the Air Traffic Controller (ATC)
  - ✓ omission of actions or inappropriate decision-reactions to events

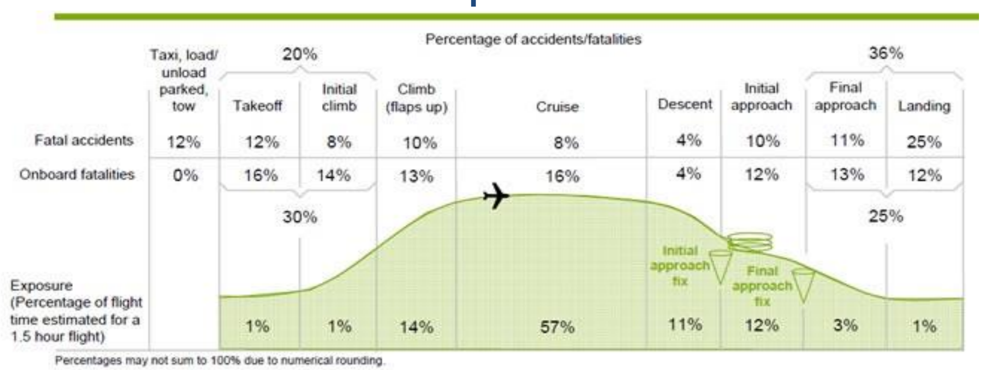


- These human factors have common roots:
  - ✓ Pilots' fatigue, stress, abnormal health conditions and training

Crew performance (especially in peak workload conditions) is **one of the major remaining limitations to Air Transport safety.**

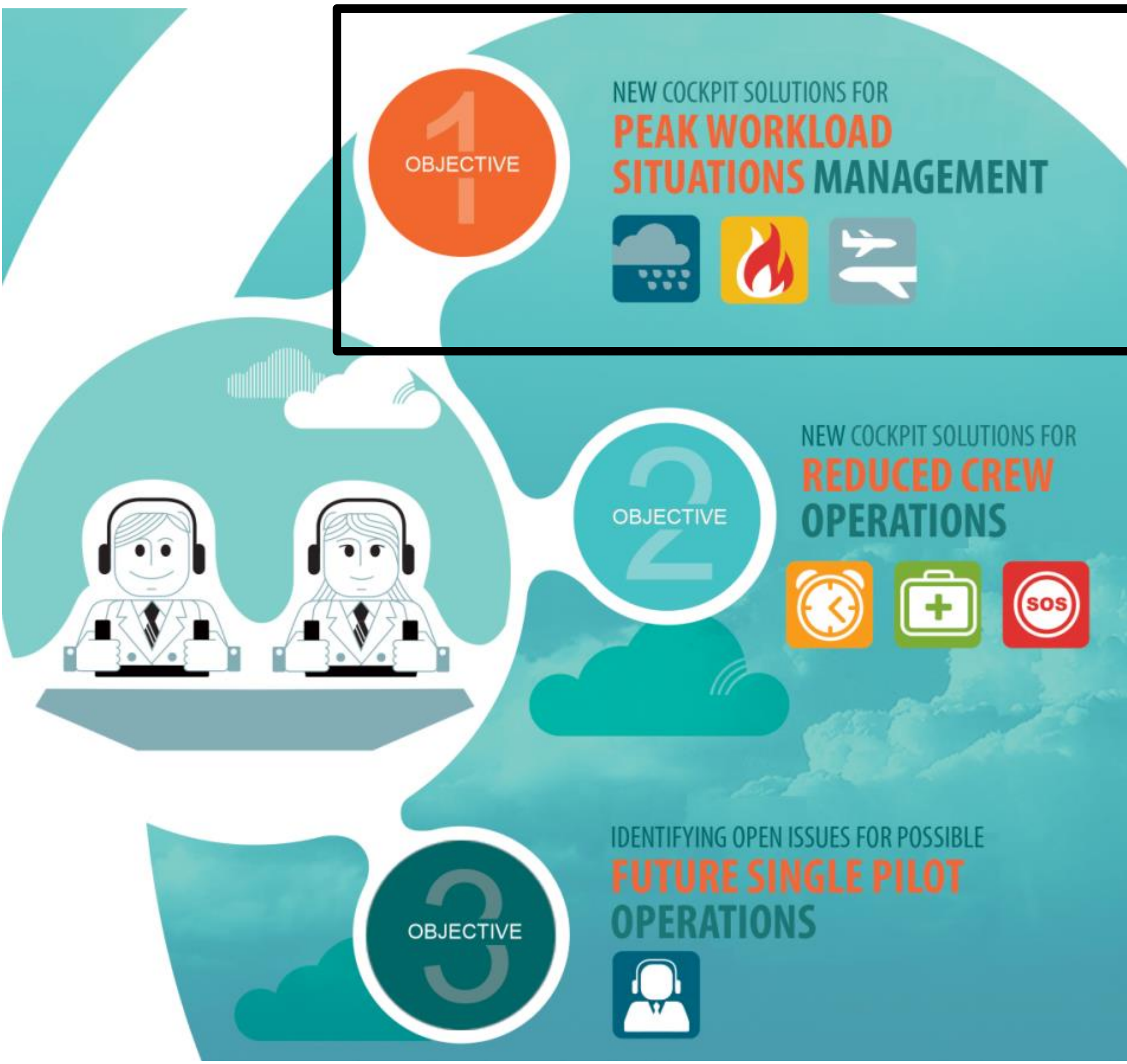
ACROSS Context

- What high workload means
  - The amount of information and actions to process may exceed the reasonably acceptable workload of the crew
- What causes high workload in the cockpit
  - Certain combinations of unpredictable situations, such as
    - Increased air traffic, new flight routes, busier airports
    - difficult meteorological conditions
    - multiple system failures
    - cockpit crew incapacitation
- When is high workload caused in the cockpit?
    - Take-off,
    - Initial Climb,
    - Final approach
    - Landing phase



- Improving crew performance in peak workload conditions is critical to enhance flight safety

ACROSS Objective 1



Design cockpit solutions alleviating crew workload in current two-pilot operations

Fully capacitated crew under peak workload

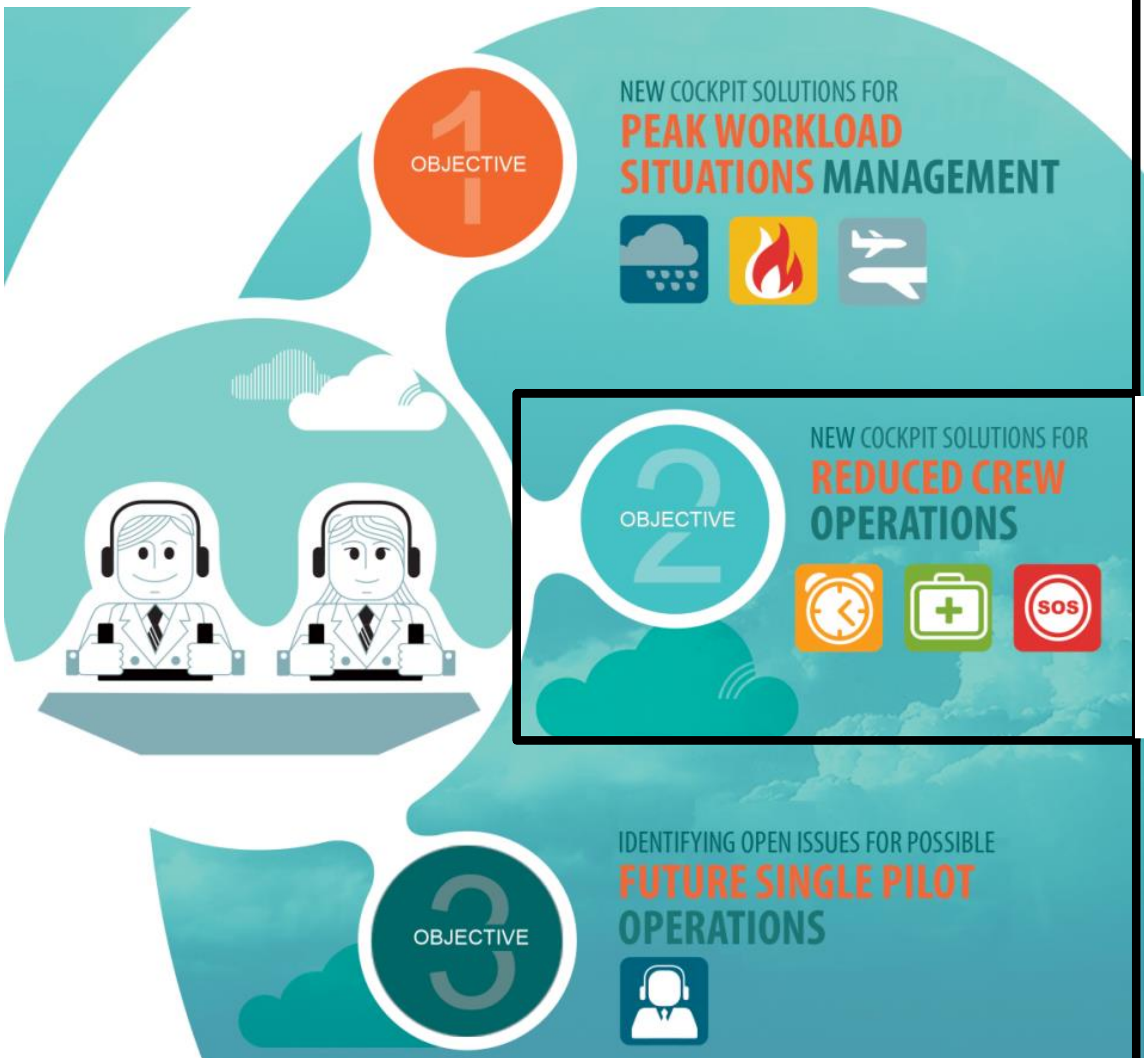
High density traffic

Bad weather

Emergencies

Improve safety** and reduce accident risks through the **reduction of stress

ACROSS Objective 2



Address incidents where one of the pilots is incapacitated

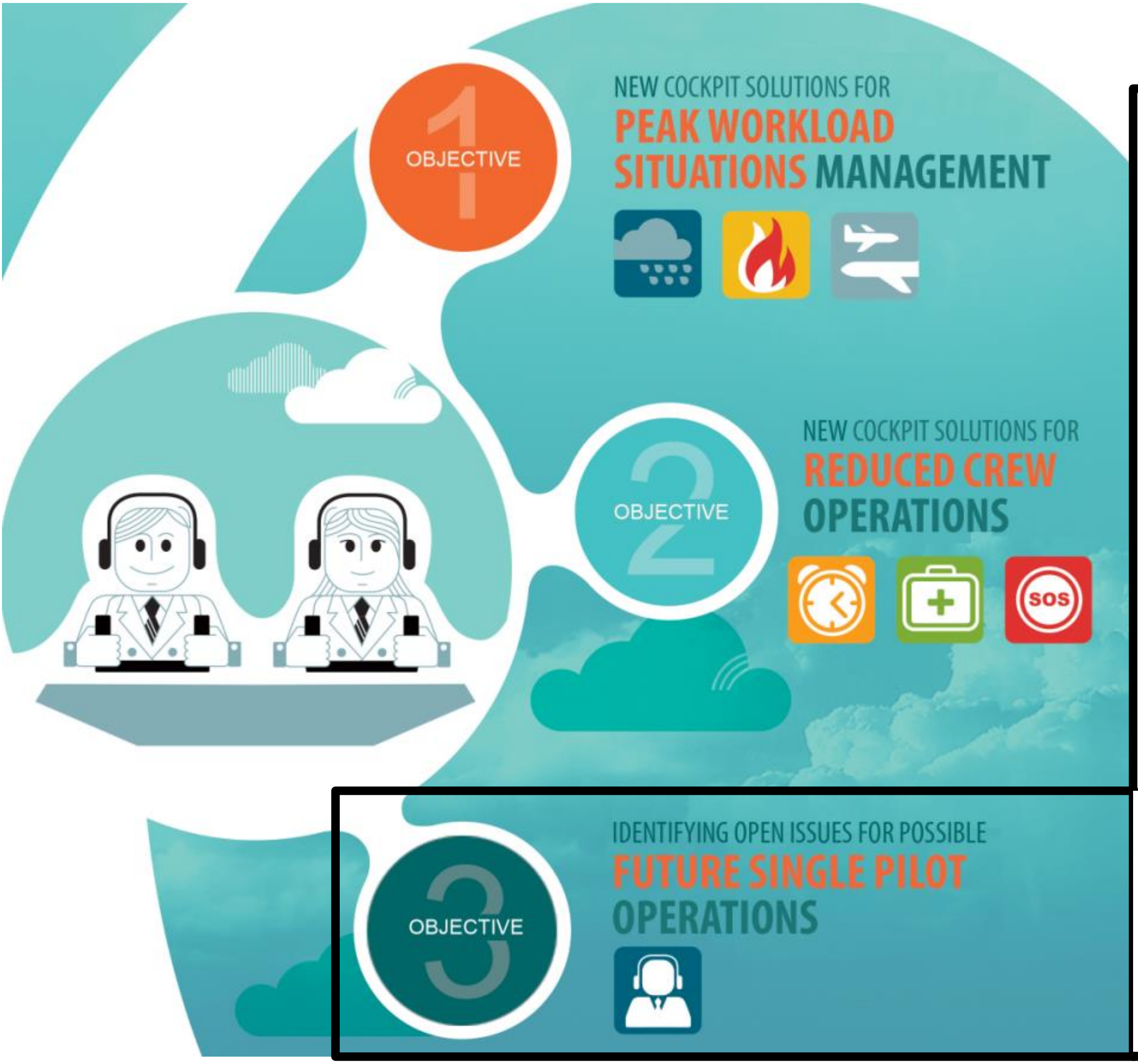
Intentionally reduced crew
Long haul flights

Pilot break during cruise phase

Unintentionally reduced crew
1 or 2 pilots incapacitated
Short, medium and long haul flights

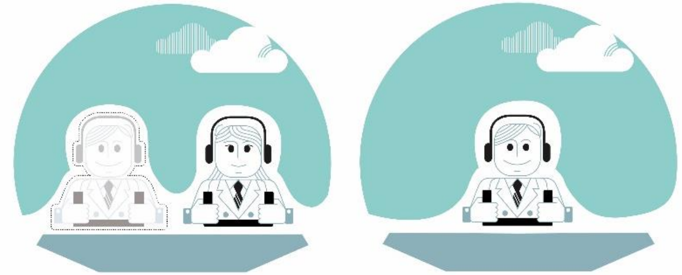
Land in safe condition

ACROSS Objective 3



Identify where possible some **open issues** for the implementation of **single-pilot operations**,

taking into account first learning about evaluations done on workload reduction (objective 1) and reduced crew operations (objective 2)



Future single pilot operations

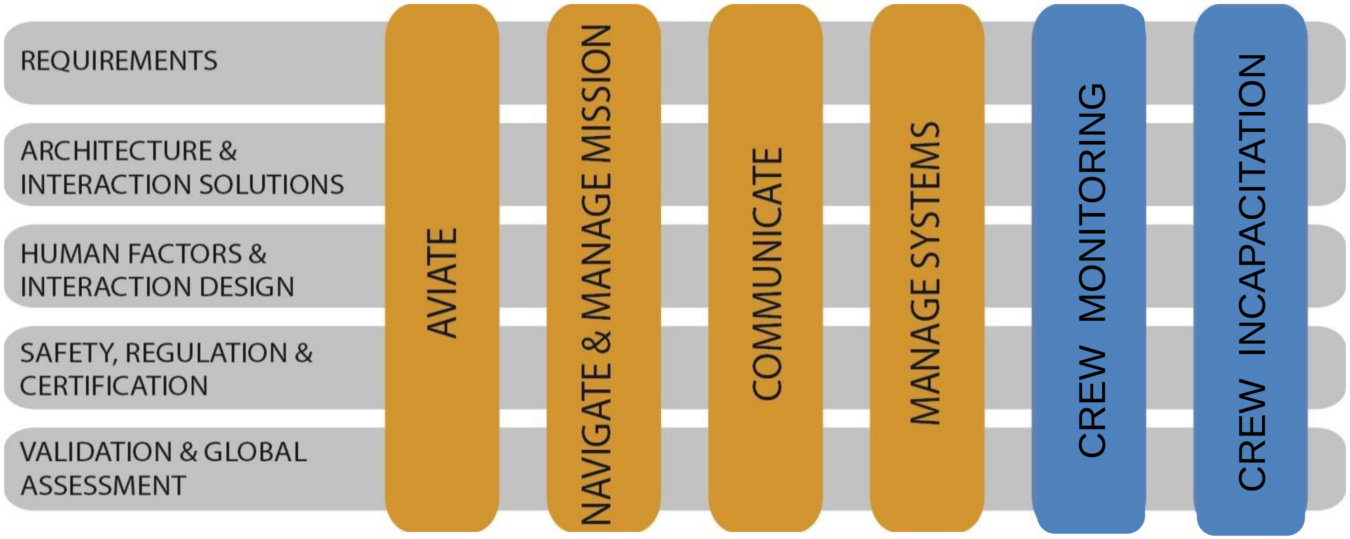
ACROSS Pillars of improve

ACROSS

- ACROSS will provide useful tools, technologies and guidelines to improve crew performance focusing on 6 pillars
  - Aviate,
  - Navigate,
  - Communicate
  - Manage Systems
  - Crew monitoring
  - Crew incapacitation

Aviate, Navigate, Communicate, Manage Systems: tasks which determine the crew's workload at any time

Crew monitoring, Crew incapacitation: technologies which can evaluate the crew's performance and support them



- Focus on Crew Monitoring

ACROSS consortium: 35 partners

ACROSS

Category	ACROSS partners
Airframers	AIRBUS; DASSAULT AVIATION; BOEING
Large Industrial Companies	THALES Avionics; BAE SYSTEMS REAL INNOVATION. REAL ADVANTAGE.; Continental; DIEHL Aerospace; Isdefe; JEPPESEN; ZODIAC AEROSPACE; THALES Training & Simulation; Selex ES; TAI; gmv
National Research Centers	DLR; NLR
Research Centers inside large Industrial Groups	EADS Innovation Works; THALES Nederland BV
Universities	TRINITY COLLEGE DUBLIN COLÁISTE NA TRÍONÓIDE; UNIVERSITY OF MALTA L-Università ta' Malta; Technische Universität Braunschweig; WARSAW UNIVERSITY OF TECHNOLOGY; TU Delft Delft University of Technology
Small and Medium Enterprises	DEEPBLUE consulting&research; TRIAGNOSYS; use2aces aviation consultants; TONY HENLEY CONSULTING; CERTIFLYER; STIRLING DYNAMICS; gtd

ACROSS consortium: 12 countries

ACROSS

United Kingdom
BAE SYSTEMS — REAL INNOVATION. REAL ADVANTAGE.
STIRLING DYNAMICS
AIRBUS
TONY HENLEY CONSULTING

Netherland
TUDelft Delft University of Technology
CERTIFLYER
NLR
THALES
use2aces aviation consultants

Poland
WARSAW UNIVERSITY OF TECHNOLOGY

Germany
TRIA GNO SYS
Technische Universität Braunschweig
DLR
DIEHL Aerospace
EADS
JEPPESEN
AIRBUS

Ireland
TRINITY COLLEGE DUBLIN — COLÁISTE NA TRÍONÓIDE

Portugal
gmv

Spain
Isdefe
gtd
BOEING

France
THALES
AIRBUS
DASSAULT AVIATION
Continental
EADS
ZODIAC AEROSPACE

Italy
DEEPBLUE consulting&research
Selex ES

Malta
UNIVERSITY OF MALTA — L-Università ta' Malta

Greece
EAB

Turkey
TAI

under the EC contract ACP2-GA-2012-314501. It is the ... consortium
... ted or reproduced without the formal approval of the ACROSS Steering Committee.

"Unrestricted PUBLIC Access"

Crew Heath Monitoring

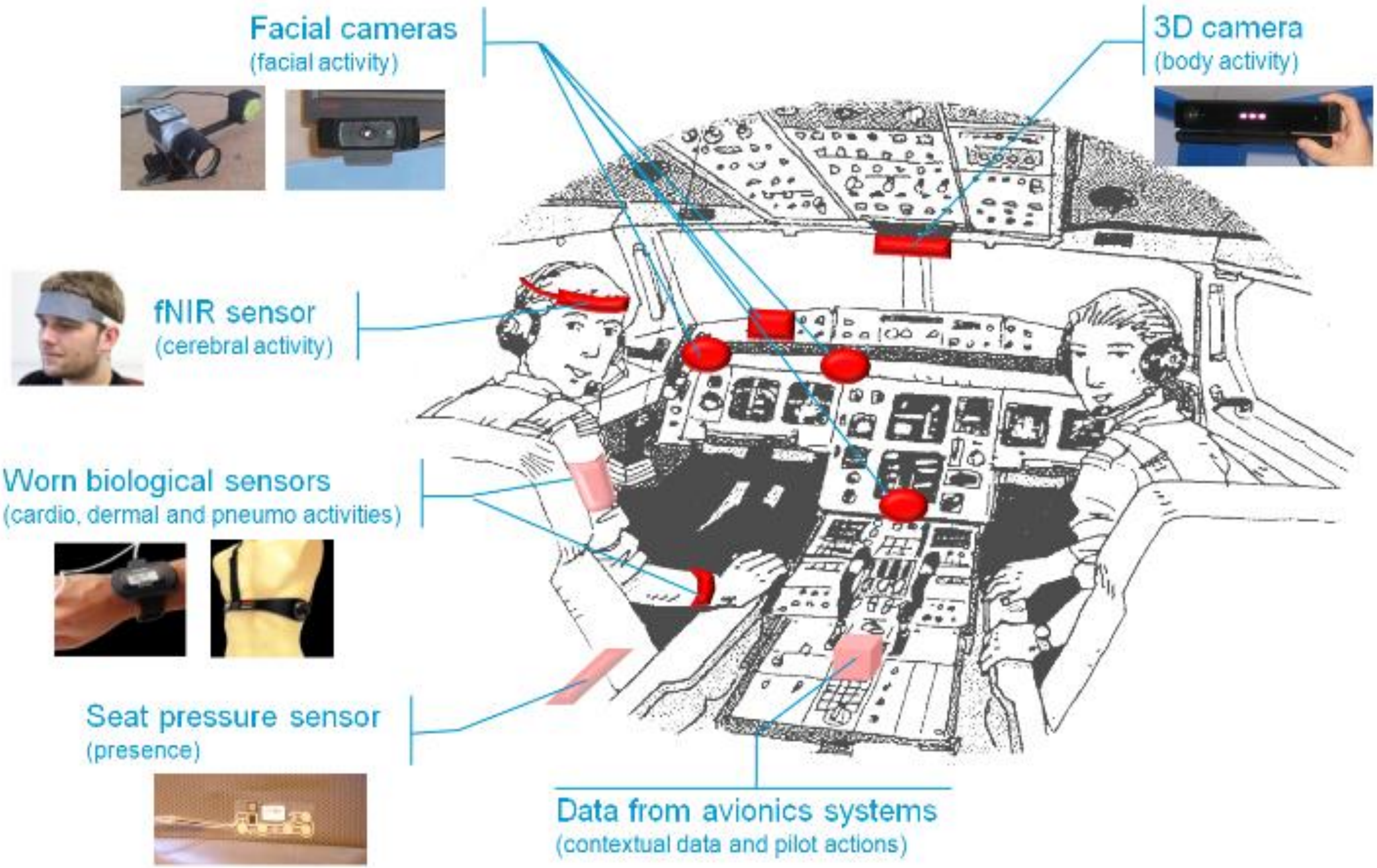
Aristeidis Nikologiannis
Hellenic Aerospace Industry (HAI)

Crew Health Monitoring Systems

The Crew Health Monitoring System is a new integrated set of crew monitoring technologies addressing:

- Presence of the crew inside the cockpit
- Total incapacitation (strokes, hypoxia…)
- Sleepiness / Drowsiness
- Distraction / Inattention to cockpit instruments
- Stress / Mental workload
- Situational Awareness (SA) / Relevance of crew activity

Candidate Technologies for Crew Health Monitoring

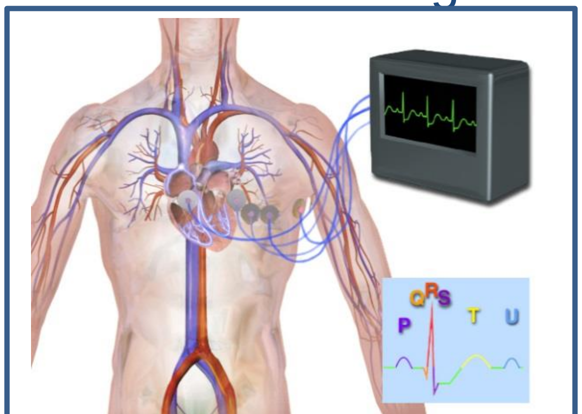


Crew Health Monitoring Functionality

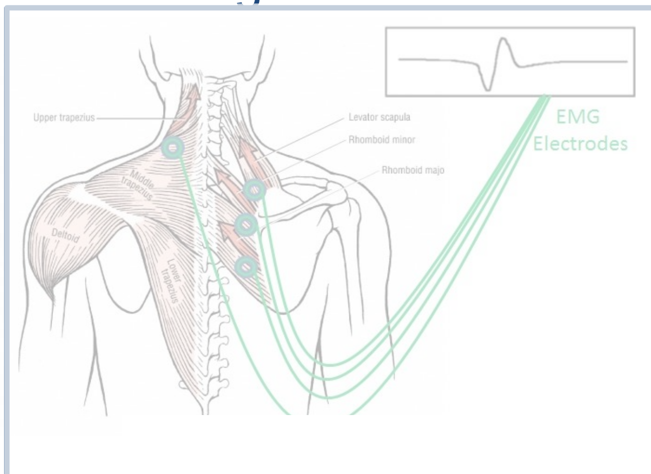
- The Crew Health Monitoring system *(in critical situations)* triggers:
  - on-board and ground-based support systems which ensure that the plane lands safely
  - functions helping the crew to focus on essentials tasks (and automating others)

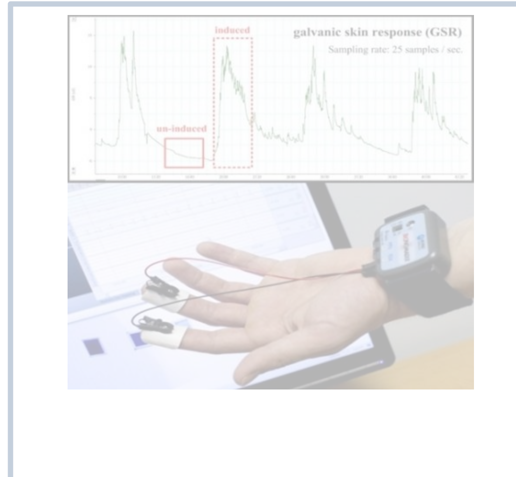
- HAI’s work focuses on body worn (wearable) devices, which can:
  - monitor crew health status through biosignals
  - make diagnosis among three health states:
    - ✓ normal
    - ✓ Abnormal due to Stress
    - ✓ Abnormal due to Life-threatening conditions, Incapacitation

- Dominant biosignals for detecting health status



Electrocardiogram



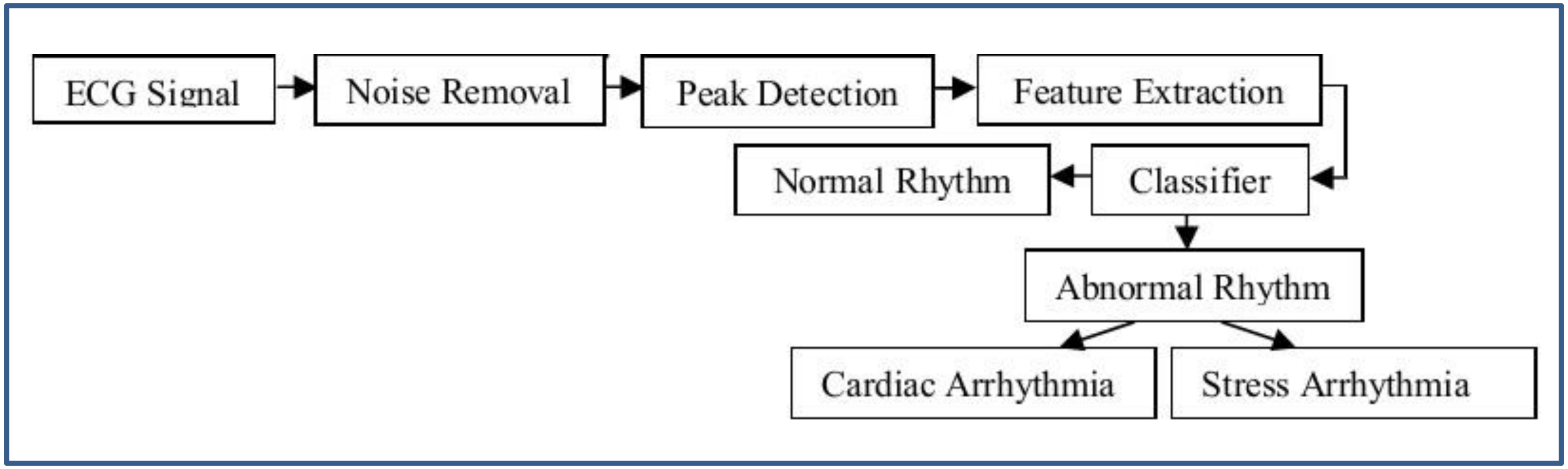


Why Electrocardiogram (ECG)?

- ECG signal was chosen because:
  - ECG is an indicator that effectively identifies health status
    - ✓ Disease, stress, fatigue, sleepiness and hypovigilance influence heart rate
    - ✓ the pattern and the range of heart rate variability would contain important information for the crew health status
  - ECG probes are non-invasive, can be easily incorporated into the pilot's suit



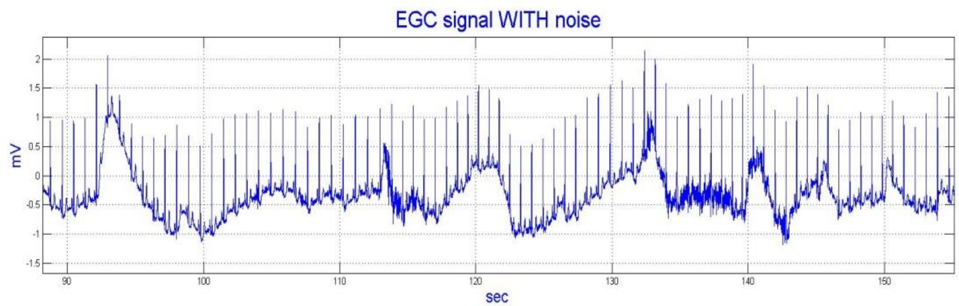

ECG body worn device architecture

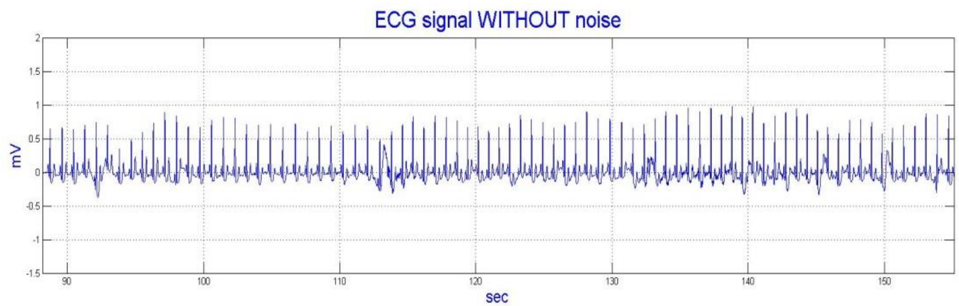


- **Data acquisition**
  - ✓ Real time ECG signals from ECG sensors
  - ✓ Non-real time ECG signals from published Databases (Massachusetts Institute of Technology – Beth Israel Hospital (MIT-BIH) Database)
- **Preprocessing**: remove the noises and detect critical points from the ECG signal
- **Feature extraction**: extract critical features from ECG to identify abnormalities
- **Classification**: Classify the ECG signal beats into
  - ✓ Normal Rhythm beats
  - ✓ Abnormal Rhythm beats
    - Life threatening - cardiac arrhythmia
    - Stress arrhythmia

Preprocessing

- The ECG signals are overlapped with noises and artefacts which lead to inaccurate diagnosis. The common sources of ECG noise are:
  - ✓ Power line interference
  - ✓ Baseline wandering due to:
    - ✓ Crew movements
    - ✓ Electrode motion artefact
    - ✓ Respiration
    - ✓ Muscle contraction noise
  - ✓ Instrumentation noise generated by cockpit electronic devices





- Remove noise with 3 FIR filters
  - ➢ remove DC and baseline wandering
    (high pass filter: stop frequency range [0-0.5Hz])
  - ➢ remove power line noise
    (band stop filter: stop frequency range [50-70Hz])
  - ➢ remove high frequency noise
    (low pass filter: cutoff frequency 100Hz)

ECG Critical Point Detection and Feature Extraction

- The critical points P,Q,R,S,T were identified using MATLAB

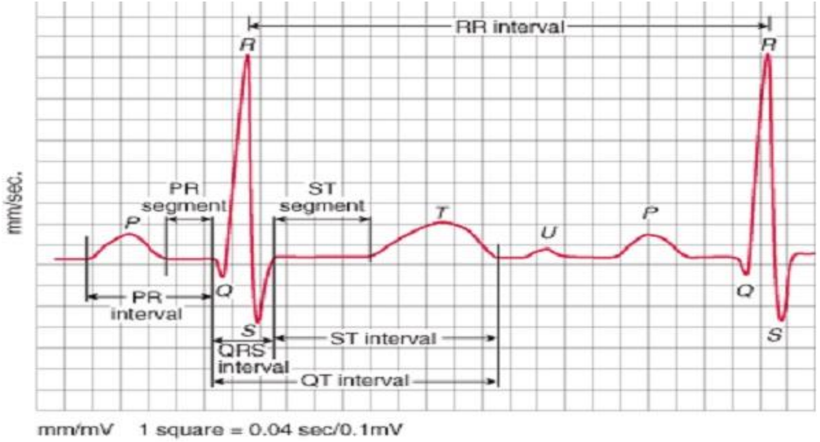


Table 1 – Classification accuracy rates for ECG features

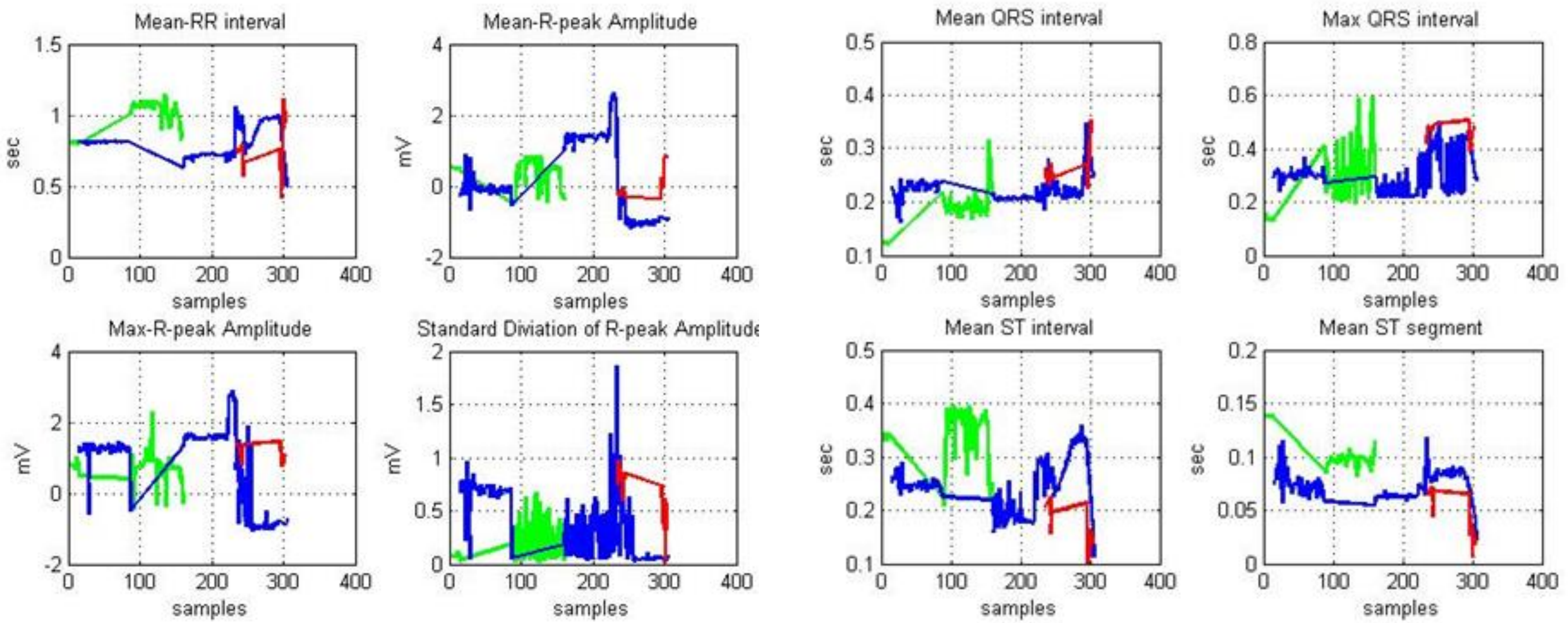
	Average (AV)	Maximum (MAX)	Standard Deviation (SD)
RR interval	75%	72%	62%
R-peak amplitude - RA	78%	76%	78%
QRS interval	79%	75%	70%
QRS complex	73%	72%	70%
QT interval	72%	71%	70%
ST interval	73%	69%	73%
ST segment	78%	73%	72%
T-Wave complex	72%	73%	75%

- A time window of 25s used for processing ECG samples and extracting the ECG features
  - ***Time domain features***
    - Define: **RR** interval, **QRS** interval, **QT** interval, **ST** segment/interval, **T-wave** duration, **PR** interval/segment
    - Estimate: Average value (**AV**), maximum value (**MAX**), standard deviation (**SD**) of the above features
  - ***Frequency domain features***
    - Estimate the Power Spectral Density (**PSD**) for normalized **(f/Fs)** frequencies in the following ranges
      - [0 - 0.04] **(VLF)**, [0.04 0.15] **(LF)**, [0.15 0.4] **(HF)**
    - Estimate the parameters
      - **SVI**: Symphatovagal balance index **SVI= LF/HF**
      - **nLF**: normalized low frequency spectrum **nLF = LF x 100 /(VLF+LF+HF)**
      - **dLFHF**: difference of normalized low frequency spectrum and high frequency spectrum **dLFHF= | nLF – nHF |**
- Select the features with the most efficient classification results as input vector to classifier
  (> 75% classification accuracy – gray shaded parameters in the right table)

Analysis of Features Extraction

- Annotated ECG signals are obtained from published databases
- Digital ECG samples are integrated into 25s time windows and features extracted
- Depiction of the features into diagrams depending on their annotation

Green line: normal heart beats, Blue line: abnormal (stress arrhythmias), Red line: abnormal (cardiac arrhythmia)



- Classification problem is non-linear: not clear linear threshold to differentiate the normal abnormal and life-threatening states.

Classification –Artificial Neural Networks

- The Classification of an Electrocardiogram (ECG) is a complex pattern recognition task
  - Large variation in the morphologies of ECG waveforms of different individuals as well as in the same person
- Artificial Neural Network (ANN) is an efficient non-linear processing tool that provides excellent classification at respectively low complexity
  - ANNs can be viewed as mathematical models of brain like systems
  - ANNs are composed of simple elements (neurons) operating in parallel. Neurons are organized into layers and layers interconnect to form a network
  - Each neuron computes the transfer function f of the weighted sum of its inputs: $O_i = f(\sum_j (W_{ij} I_{ij}))$
- ANNs classify input data into categories, provided they are previously trained to do so
  - The knowledge gained by the learning process is stored in the form of connection weights, used to classify the real time input data

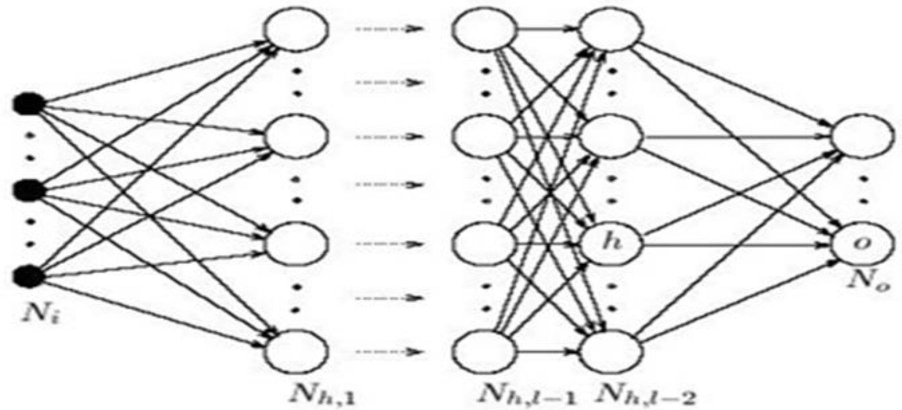


Fig 1. The Structure of the neural network (feed-forward)

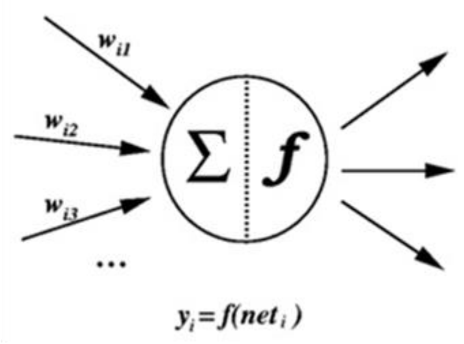
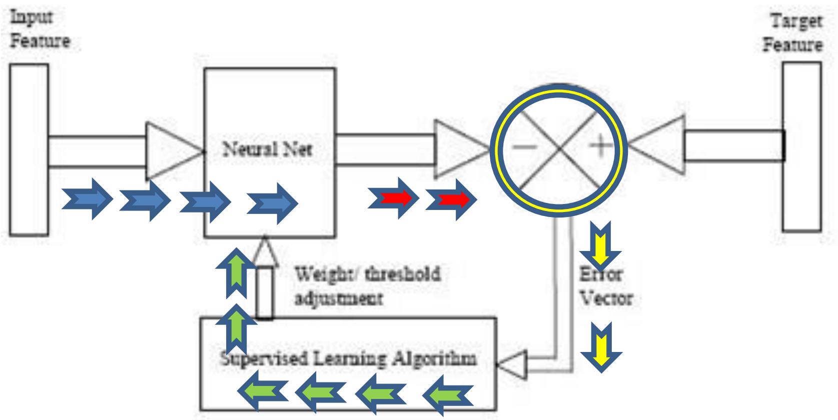


Fig 2. The structure of a neuron

Neural Network Training and Testing

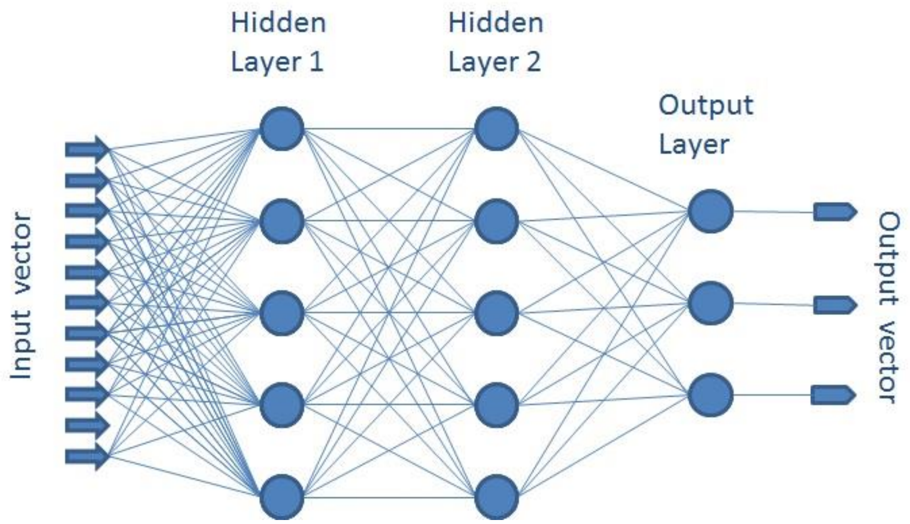
- Supervised, Back Propagation Training
  1. Input – target Output vector pairs required
  2. Propagate the input vector through the feedforward network
  3. Compute the output vector
  4. Compare the output vector with its desired value, resulting in an error vector
  5. This error vector is propagated backwards to modify the weights of the neurons
  6. This process (steps 1 to 4) is being repeated until the system error reaches an acceptable limit



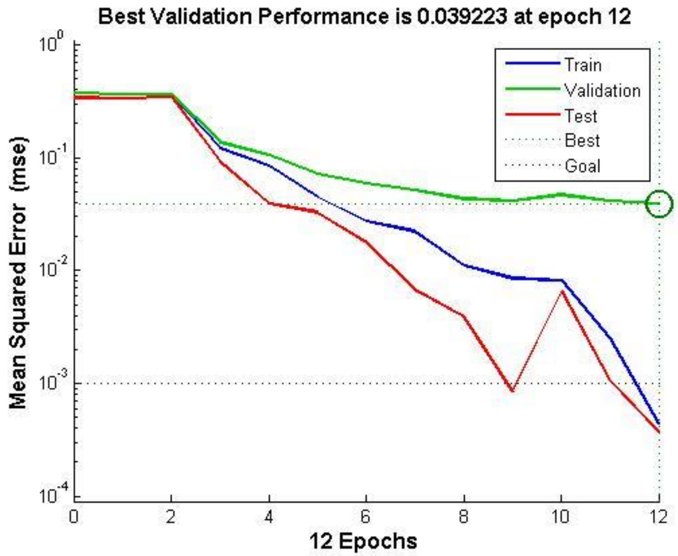
- Train & Test the ANN classifier using data from the ECG database for:
  - Normal ECG Rhythm
  - Abnormal (Stress Arrhythmia) ECG Rhythm
  - Abnormal (Life-Threatening Arrhythmia) ECG Rhythm

The Artificial Neural Network Classifier Results

- We defined the optimal ANN for classifier with the following attributes
  - Multi element input vector-**ECG features**
  - Multi-layer feed forward structure
  - Output vector with 3 elements
  - Back-propagation learning algorithm



- ANN Training performance

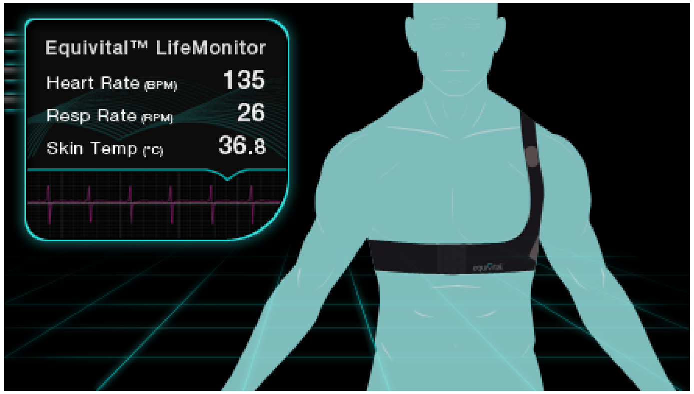


- ANN Classification performance

	Sensitivity (%)	*Specificity (%)*	*Accuracy (%)*	*MSE (%)*
Normal State	95.3278	96.8773	96.0777	3.2070
Abnormal State	95.5634	97.2760	96.5815	2.9606
Life threatening State	85.7798	98.9067	97.8769	1.9675

Development

- The Equivital™ LifeMonitor multi-parameter body worn sensor system used as the development platform
  - Supported sensors:
    - ECG, Heart rate, Respiratory rate,
    - Skin temperature, Accelerometer X,Y,Z
    - Oxygen, Galvanic skin response

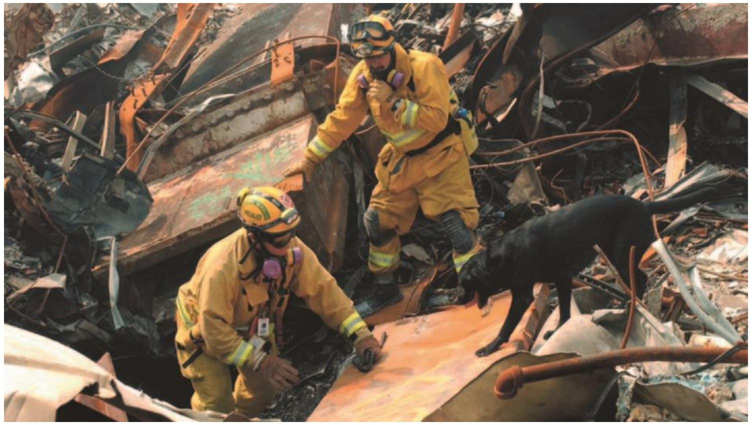


  - It senses, processes, stores and transmits human biophysical data
  - SDK software package helps to integrate the development platform into across health monitoring platform

Exploitation

- Modify the body worn sensor system to a wearable sensor array, fitted in uniform for monitoring the health of workers employed in hazardous activities

Firefighters



Rescuers

Cleaning of fuel/chemical tanks

Mining workers

Conclusion

- ACROSS overview
  - New technologies and novel Avionic architectures in cockpit to improve safety, reduce accident risk through the reduction of workload and stress

- Crew health monitoring system
  - Candidate sensor technologies to future cockpit
  - Body worn devices with biosensors (ECG)
  - Architecture of an ECG body worn device
  - ECG features extraction
  - Crew health status classification
    - ✓ Neural Network Overview
  - Development Platform (Equivital^{TM} LifeMonitor)
  - System exploitation

Advanced Cockpit for Reduction Of Stress and Workload
ACROSS (314501)

Project co-funded by the European Commission within the
Seventh Framework Programme (2012-2016)