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Catalogue of solutions and explanation for 3rd party applicants

Work Package 4

Open Call setup, implementation & selection of Application Experiments

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EXECUTIVE SUMMARY

This document presents the building blocks (technological bricks) proposed by EARASHI partners in the context of EARASHI open calls. It corresponds to the building block portfolio as available on EARASHI website at: <https://earashi.eu/building-blocks/>



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1 INTRODUCTION

EARASHI project, HORIZON Europe, aims to improve working conditions, trust, and acceptance of collaborative embodied AI in robotic systems, for the production machines/tools sector. This will be achieved by supporting Industry, especially start-ups and SMEs, in the uptake of advanced digital and eco-responsible technologies (in particular AI, data, and robotics). This approach will help employees in their daily activities and improve their working conditions, leading to a productivity increase. EARASHI adopts a worker-centric approach by considering workforce well-being and health (e.g., MSD and stress), design thinking methodology of production machines, worker acceptance, and ethics.

EARASHI will set-up and publish 2 open calls (M6 and M13) with focus areas and challenges to improve working conditions in the production machines field -health, safety and well-being- and increase productivity via human-centred collaborative embodied AI, data & Robotics. The 10 selected projects/beneficiaries will:

- benefit from Financial support to Third parties (FSTP, Cascade funding) – up to 200 k€ (100% funding rate for Start-Ups and 70% for SMEs);
- get access to EARASHI leading-edge technologies (BB) and test facilities from RTOs and industrial partners, business support, mentoring by industrial pairs, support in ethics, system integration, and user acceptance, thus lowering both their technical and business barriers.

EARASHI targets to:

- fund 10 projects;
- foster pan-European collaboration with at least 50% of selected projects being cross-border;
- enable agile responses to urgent needs and open strategic autonomy in digital and future emerging enabling technologies, with 80% of the selected AEs having market potential, and more than 20% of the selected AE reaching TRL8-9 two years after the end of their project.

To that purpose, by means of the open calls and the FSTP, EARASHI partners will provide access to Technological BB and Key Competencies for the selected application experiments. The foreseen BBs available through the open calls (technology transfer support) and the key competencies that will be provided to the granted projects.

The deliverable D4.2 presents the catalog of BB proposed by EARASHI partners, provided breakthrough technologies to bring answers to the open call challenges. This catalog is also available on EARASHI website at <https://earashi.eu/building-blocks/>.

2 BUILDING BLOCK CATALOG

The deliverable D4.2 presents the catalog of BB proposed by EARASHI partners, provided breakthrough technologies to bring answers to the open call challenges. This catalog is also available on EARASHI website at <https://earashi.eu/building-blocks/>.

The building block catalog introduces 23 leading technologies covering AI, Data and Robotics domains sorted as so to ease their access by the open call applicants.

Each BB presentation and description has been prepared by the technology owner on time and the catalog was made available on EARASHI website at the call opening.

All 23 BBs were available for EARASHI open call 1. Following the Open Call 1 selection of 5 projects, some of the building blocks may not be available for the 2nd open call. This will be clearly indicated on the online catalog with the mention “**NOT AVAILABLE, ALREADY USED IN OC1**”. BB1 will be removed from the catalog as it was not selected through OC1 and will not be available for OC2.

The 6 partners providing building Blocks are the following. Each BB owner is identified thanks to its logo. A technical contact is available to answer any question on the presented BB.





BB1: STRESS OBERVER

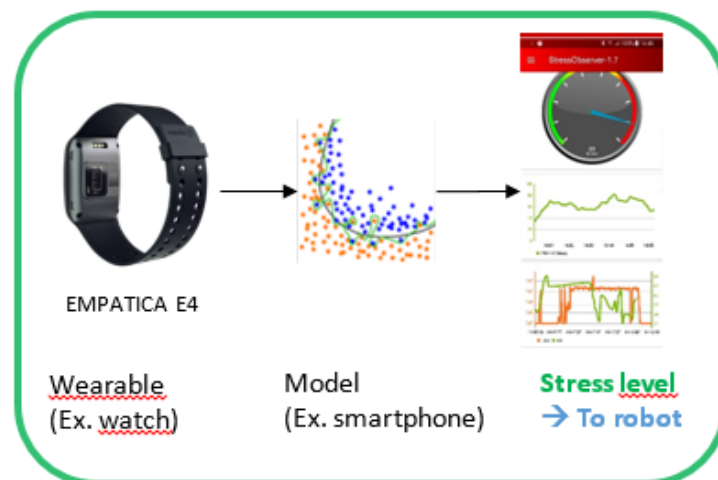
Building block “Stress Observer” allows to evaluate mental stress level (acute stress) of a person in real-time.

It was initially developed for the European project “BonVoyage” to evaluate traveller’s stress depending on used means of transport.

Physiological measurements, such as galvanic skin response, blood volume pressure or temperature are collected by an off-the-shelf connected watch worn by the person. These measurements are sent by Bluetooth link and processed using machine learning models to calculate a stress score. The building block can be run and displayed in real-time by an Android application but can also be run on a PC as it is developed in Python language. Actually, the system uses the Empatica watch as wearable, which needs to have an internet connection in the surrounding area to launch measurements. In case of smartphone use to receive data, Wi-Fi connection or PC connection is needed to download measurement files for further analysis.

The system’s advantages are real-time, wearability and mobility. Thus, stress level of the operator could be estimated during all different working tasks without obstructing in ambulatory scenarios. Detecting the operator’s stress when collaborating with robots allows to adapt robots’ behaviour and then enhance the well-being of the operator. Several commercial smartwatches which give stress indicators already exist. However, they do not provide real-time assessment of stress. Moreover, it is not possible to identify if those smartwatches provide acute or chronic stress. With this building block, acute stress level, which is relevant during robot and human interactions, is provided. As the temporal resolution is higher with this solution, the consequences of the robot’s actions on human stress could be accurately analysed.

This building block can be used in situations where there is a will to improve physical and mental working conditions and the safety of operators.



For more information, please contact:

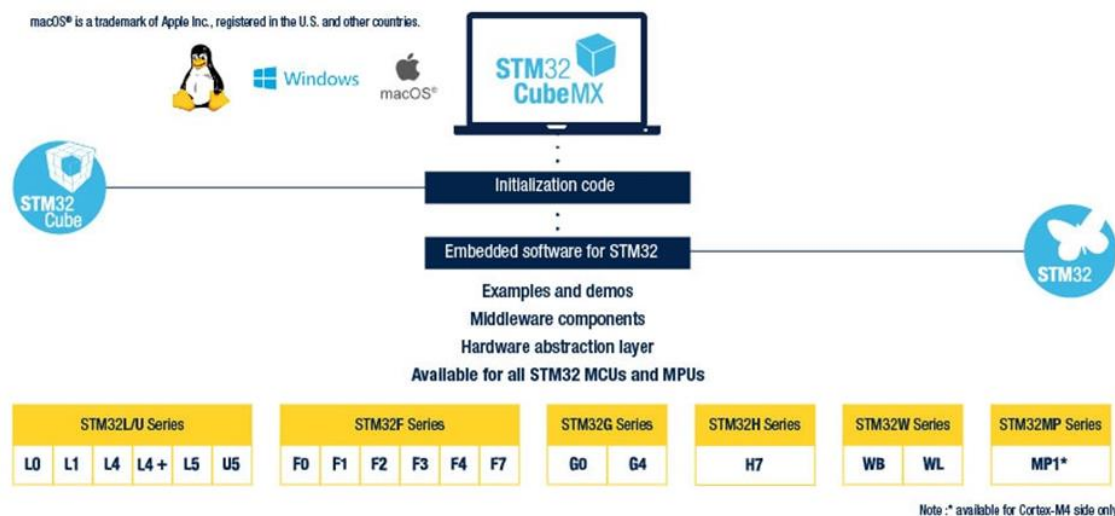
Claire Guyon-Gardeux : claire.gardeux@cea.fr

BB2: Motor Control Software Development Kit

STM will provide STM32 microcontroller and/or microprocessor to enable to implement end user applications or system. To In case that the end user does not plan any development STM32 board, ST will provide fast prototyping solutions such as the STM32 nucleo or discovery kits boards. To Speed up the development of an embedded project and to avoid time-consuming software development from scratch, with all the constraints that come with it. ST will give free access to the STM32Cube. STM32Cube is a proven software suite with direct access to many components ensuring interoperability and seamless reusability.

Using STM32Cube, end users can have access to MCU and MPU Packages for each individual STM32 MCU and MPUs series that include:

- The hardware abstraction layer (HAL) enabling portability between different STM32 devices via standardized API calls.
- Low-layer (LL) APIs, a lightweight, optimized, expert oriented set of APIs designed for both performance and runtime efficiency
- A collection of middleware components including RTOS, USB library, file system, TCP/IP stack, touch-sensing library or graphics library (depending on the STM32 series)
- RF stacks such as Bluetooth® LE 5.2, OpenThread, Zigbee 3.0, LoRaWAN® and Sigfox, specific to every STM32 wireless series
- For STM32 MPUs only, the BSP drivers are based on HAL drivers and provide an API Set to the evaluation board and 3rd party components.



Today, embedded hardware devices need to perform more complex AI tasks Therefore ST will provide also the STM32Cube.AI is a free software tool to import and convert pre-trained Machine Learning or Neural

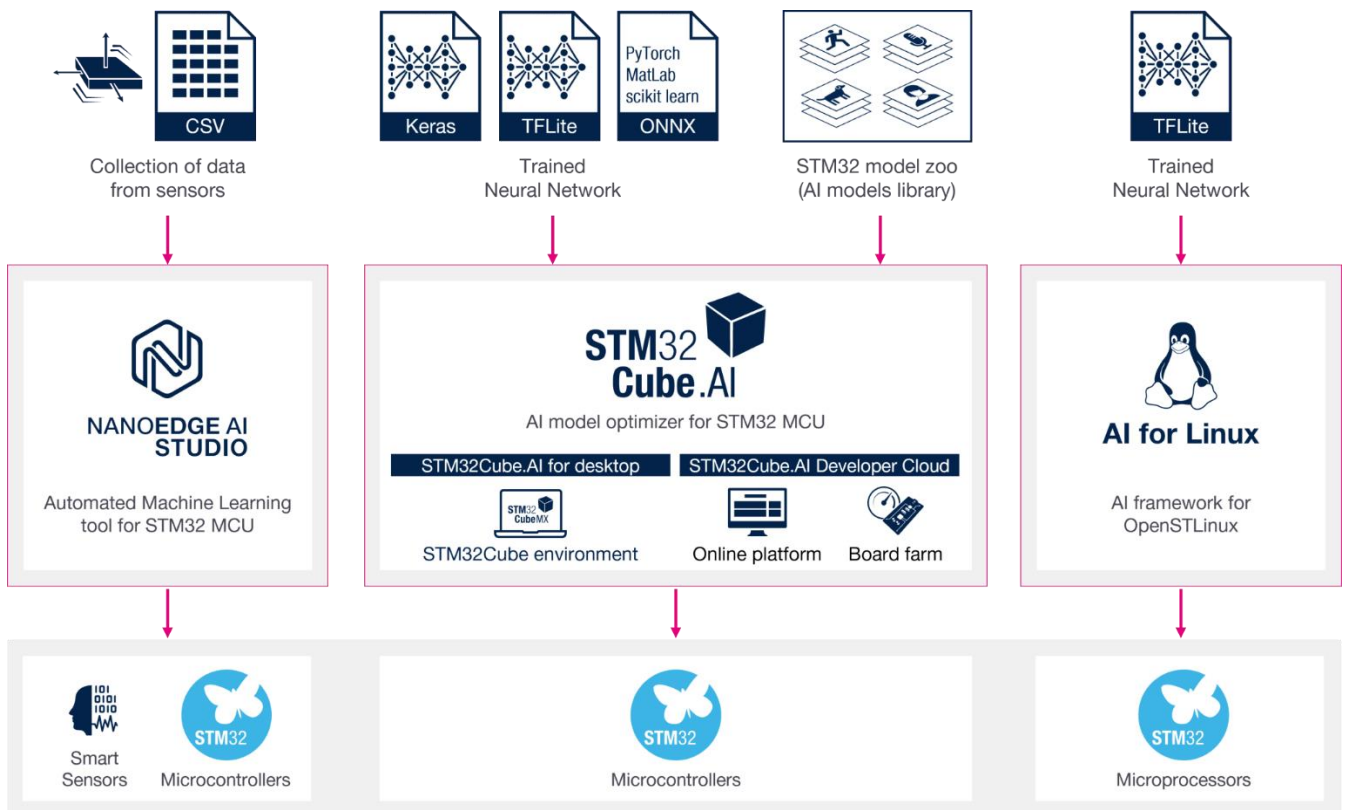
Network models into optimized C code for STM32. STM32Cube.AI is a tool for users who have prior experience in creating and training deep learning NN models in frameworks such as TensorFlow Lite, Keras, qKeras or Pytorch.

For more information, please contact:

Marcello Coppola - marcello.coppola@st.com

BB3: Artificial Intelligence Solutions

STM will provide several AI solutions for STM32 and smart sensors, so you can find the right fit for your project, depending on your resources, needs, and workflows. STM will offer several tiny ML solutions to embed AI on microcontrollers, microprocessors, and smart sensors. Our extensive offer in the BB3, allows people to find the right tool for your project, regardless of your level of expertise in machine learning.



With NanoEdge AI Studio, people can easily generate ML libraries for your embedded devices, with millions of pre-built models available. This means that people do not need to collect and document large and complex data sets. Thus, model can also be self-trained on your device. For experimented people that have AI knowledge, STM32Cube.AI will automatically optimize your trained artificial neural networks and generate the corresponding C-code for STM32 microcontrollers. STM32Cube.AI tool helps to optimize performances and memory footprint of trained AI models in your STM32 project. It supports TensorFlow™ Lite, Keras and ONNX formats. It is available in desktop version or directly online via the STM32Cube.AI Developer Cloud. The online platform features a benchmark service to remotely evaluate AI performance on a selection of STM32 boards. In addition, get access to STM32 model zoo that gathers a collection of optimized AI models, some application examples, training scripts and much more.

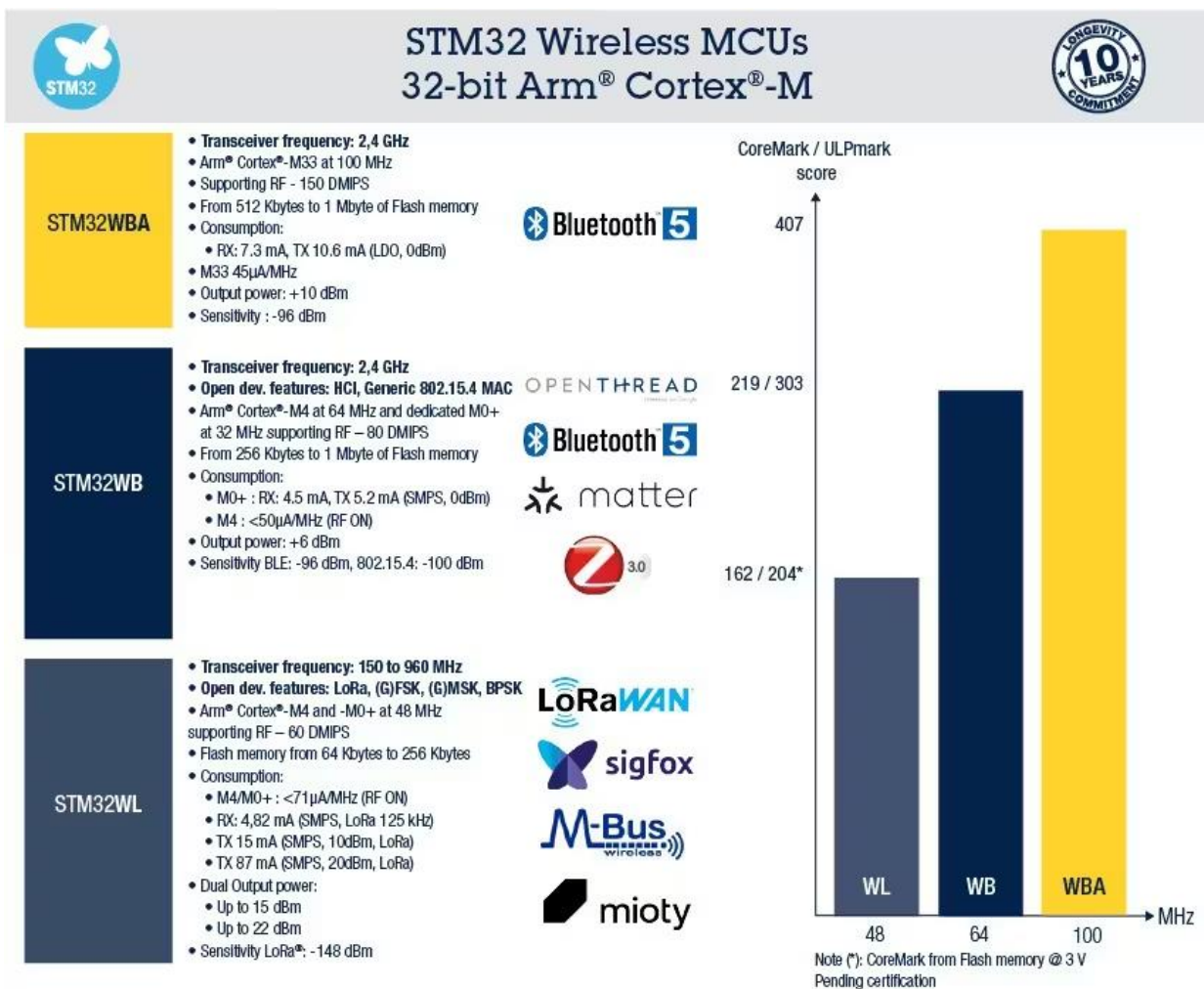
Finally, for developers who work with OpenSTLinux, we have developed a complete framework allowing to easily integrate AI models.

For more information, please contact:

Marcello Coppola - marcello.coppola@st.com

BB4: IIoT Connectivity

STM will provide STM32 microcontroller and/or microprocessor to enable to implement end user applications or system In particular the STM32Wx microcontrollers enable wireless connectivity. They support the sub-GHz band and the 2.4 GHz frequency range. Highly integrated and reliable, they address a wide range of industrial and consumer applications. STM32Wx solutions are compatible with multiple protocols, from point-to-point & mesh to wide-area networks. They are power efficient and offer built-in security features. TM32Wx wireless MCUs feature a two-in-one, dual-core architecture. Built around an MCU and a radio transceiver, STM32Wx MCUs come in one deeply integrated and highly cost-efficient System-on-Chip. STM32Wx solutions enable real-time performance while ensuring efficient power consumption.



By choosing ST and in particular the BB4, selected application experiment can rely on our wireless expertise and a long-term partnership.

For more information, please contact:

Marcello Coppola - marcello.coppola@st.com

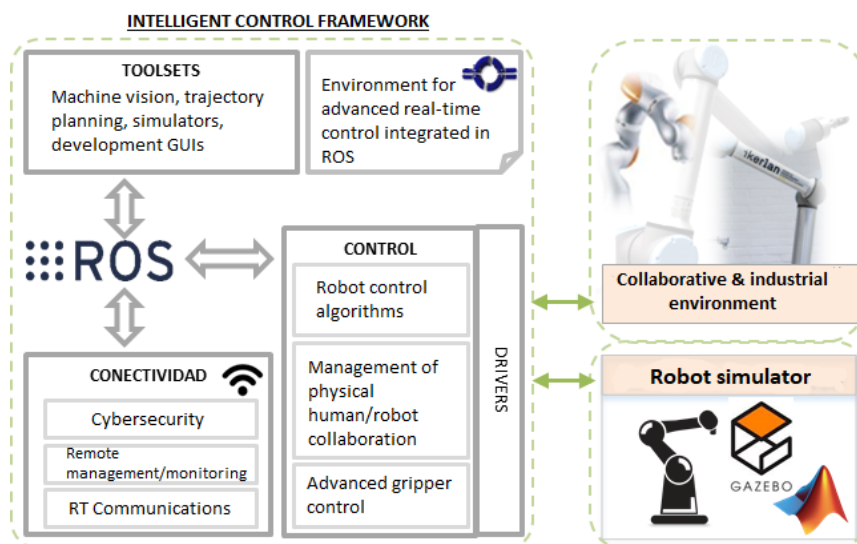
BB5: Robot Intelligent Control (RIC)

The RIC platform enables fast integration and deployment of novel mechatronic applications. Within this platform tools and libraries that allow interfacing with various robots can be found (KUKA, UR, etc.). These robots can then communicate with the heterogeneous technologies and systems through the ROS/ROS 2 middleware layer over both wired and wireless physical communication layers. On top of this, APIs and OS images are available for creating real-time (RT) compliant controls and applications within the platform.

Over these core components, implementations are also available of deep learning and collaborative control algorithms for mobile and static robotic manipulators. These algorithms are based on developments in paradigms such as artificial potential fields (APFs), deep reinforcement learning control (Deep RLC), and both classic and artificial intelligence-based computer vision. For the virtual validation of the applications simulation support packages are also available for the Gazebo simulation environment. In addition, Intel offers the RealSense family of cameras consisting of stereo depth, LiDAR, tracking cameras, and facial authentication solutions, which are specially designed for application in robots as it provides wrappers for integration into ROS / ROS 2.

The platform, through the ROS and ROS 2 client libraries, allows the development of user code in C++ and Python among others. The OS used is a Linux system built around the well-known Ubuntu 20.04 LTS distribution. Supported hardware includes standard (x64) GPU-accelerated computers and the Nvidia Jetson series devices.

Among many other possible use cases, this platform could be useful in the development of mobile robotic assistants for industrial operations such as screwing and assembly. However, the flexibility of the platform allows it to be implemented in a wide range of applications involving robots.



For more information, please contact:

earashi@ikerlan.es

BB6: MBD Simulation

MBD simulation is a novel methodology for studying the impact of clearance increase in the structural life or fatigue assessment on robotics through Multi-Body Dynamic analysis. A simplified method based on popular commercial software is proposed to analyse the effect of clearance evolution on the service life of robots, which requires low effort from the user, thus being a suitable tool industry. This simulation method has been developed to be able to estimate the degradation of the joints (wear) depending on the operational use (loads) and estimate the non-linear evolution of the degradation mode. In this way, it is possible to evaluate how the performance of a system (precision or fatigue) can vary during its use phase and estimate the service life of a mechanism. The solution is a physical model-based library element running in MATLAB and is capable to run embedded into a multibody simulation.

This solution could be particularly interesting for users who want to evaluate the performance of robotic or manipulator solutions in terms of precision and fatigue, as there is no other commercial alternative at present. Among many other possible use cases, this solution could be useful in the development of mobile robotic assistants for industrial operations such as screwing and assembly.

In order to implement the MBD simulation, it is necessary for the interested parties to have a MATLAB environment (and hardware powerful enough to run it), although standalone executable models can also be provided. To facilitate implementation, support is provided in the development of the physics-based model and evaluation.

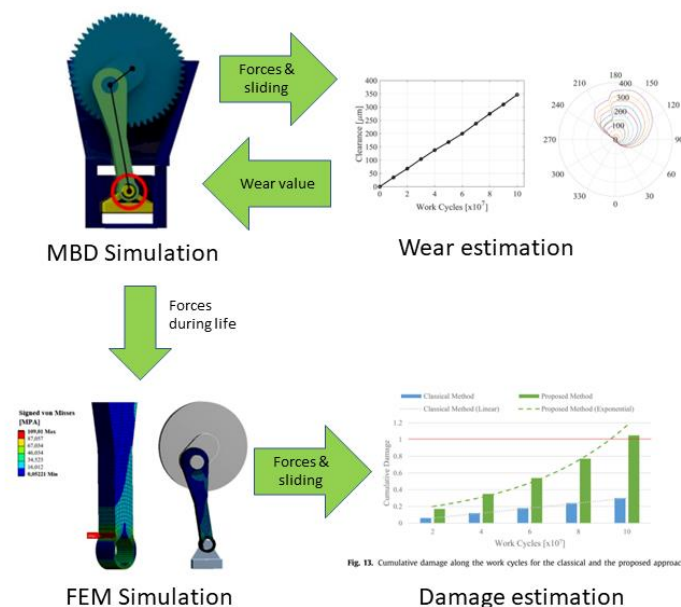


Fig. 13. Cumulative damage along the work cycles for the classical and the proposed approach.

For more information, please contact:

earashi@ikerlan.es

BB7.1: KONNEKT - GYDA

Linux is a family of open-source Unix-like operating systems based on the Linux kernel, an operating system kernel first released on September 17, 1991, by Linus Torvalds. Linux is typically packaged in a distribution that includes the kernel and supporting system software and libraries, many of which are provided by the GNU Project. Many Linux distributions have been created, such as Ubuntu, Debian, and CentOS. It is estimated that 96.3% of the world’s top 1 million servers run on Linux and 90% of all cloud infrastructure operates on Linux and practically all the best cloud hosts use it. GNU/Linux is also widely used in embedded systems such as cell phones, TVs, set-top boxes, car consoles, smart home devices, industrial control equipment, and more. Linux is increasingly becoming more popular for commercial embedded industrial applications. Several key advantages make Linux a worthwhile investment for an embedded development project: Robustness, Scalability, Widespread acceptance, Low cost, Easy customization, and Ready support.

To accelerate developments and reduce costs and time-to-market, a custom embedded **GNU/Linux** distribution called **GYDA** has been developed, that natively provides, applying secure-by design principles, a given set of security capabilities to fulfil **SL 1** requirements established by the [IEC 62443-4-2 standard](#). GYDA aims to build **composite products** from this pre-evaluated SW component to be used as a reusable block. This composition enables the reuse of assurance evidence and, consequently, reduces the amount of work to be done for the certification of the composite product. For its implementation and composition, the Yocto Project is used. The Yocto Project splits large software modules into layers. Hardware manufacturers typically provide a BSP layer for their products, complete with drivers and kernel configuration. The embedded specialist then adds a custom layer that inherits the hardware layer, adding and removing components to fit the product. The **GYDA** layer will provide security capabilities and technical measures. Figure 1 shows the reusability concept of **GYDA**.

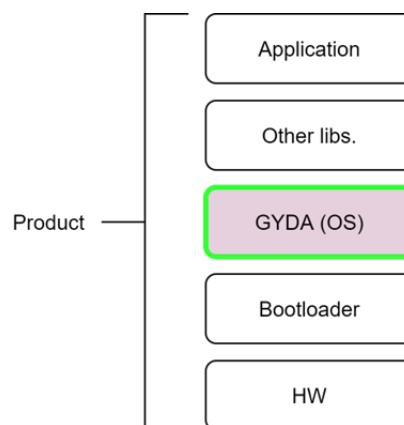


Figure 1: GYDA OS reusable SW block

For more information, please contact:

earashi@ikerlan.es

BB7.2: KONNEKT – MODHIST

MODHIST (Modern Data Historian for Industrial Data Fabric Component) is a modern data historian concept for industrial digital platforms, based on new distributed and time-series data-oriented software technologies.

MODHIST aims to access and integrate data collected from industrial processes to improve and make faster data-driven process decisions. Typically, a data historian writes and reads streaming time series data in production, collecting real-time process data from process control systems, sensors, equipment, and other data. The goal of this type of solution is to support analytics and decision-making and digital transformation by storing data on-site, in the cloud, on the edge, or in a data lake, for an enterprise.

MODHIST is a software system that records and retrieves production and process data by time; it stores the information in a time-series database that can store data efficiently with minimal disk space and fast retrieval of information. Time series information is often displayed in a trend or as tabular data over a range of time (e.g., last day, last 8 hours, last year, etc.). MODHIST offers much higher levels of efficiency than other data historian systems could offer with more traditional technology.

MODHIST is based widely known open source for connectivity and data ingestion (through MQTT Broker), data processing (through data processing pipelines), and data storage for a high volume of event data (through a time series database). MODHIST is compatible with other visualization tools (such as Apache Grafana) so that data stored in the database can be visualized with 3rd party tools.

To be able to run MODHIST, it is recommended to have generic two machines with a Linux-based Operative System installed (CentOS 7 recommended), each with a minimum of 1 CPU 3,0 GHz and 2GB of RAM. Both machines need to have Docker¹ and Docker-compose² utilities installed.

For more information, please contact:

earashi@ikerlan.es

¹ Docker - <https://www.docker.com>

² Docker-compose <https://docs.docker.com/compose>

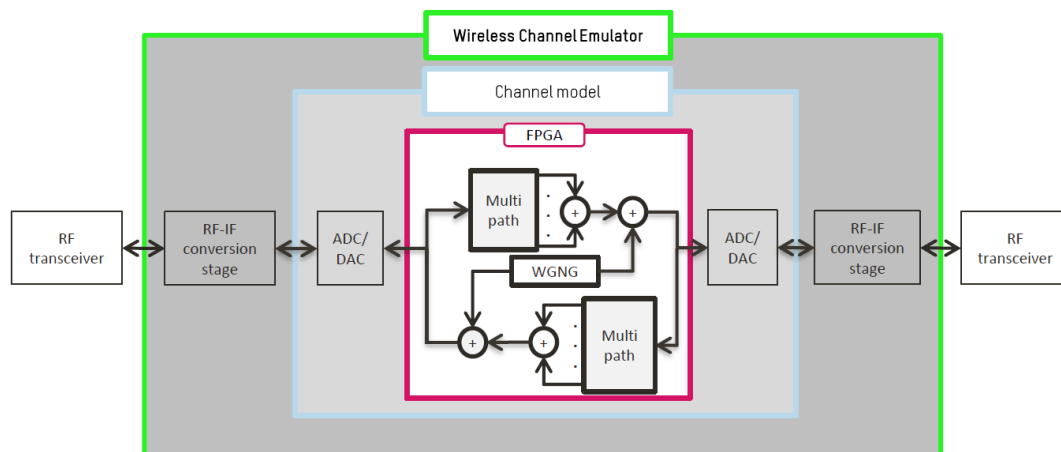
BB7.3: KONNEKT – WIRELESS CHANNEL EMULATOR

A channel or propagation emulator is a device that provides a controlled and repeatable environment where radio transmitters and receivers can be tested in different propagation conditions. This is especially important for those applications where radio devices need to operate in environments where strong multipath or fast-changing scenarios can compromise the quality of the wireless link (e.g. scenarios with high mobility, metallic scenarios, etc.). This is the case with Wireless Sensor Networks (WSN) installed in industrial environments, such as factories or transportation systems (railway, aeronautics, etc.).

In order to use the channel emulator, the antennas of the radio devices need to be replaced by coaxial cables and connected to the RF ports of the channel emulator. Once a specific propagation channel is configured in the emulator, the radio devices will ‘see’ the radio signal as if they were actually operating in that specific propagation environment. This allows testing radio devices in a controlled and realistic way, avoiding the high cost and practical issues of field validations.

The channel emulator achieves this transparent behaviour by down-converting first the signal of the transmitter device to lower frequencies, then digitizing the resulting signal, and finally applying with an FPGA the characteristics of the selected propagation channel. Afterwards, the signal is up-converted again to RF frequencies so it can be sent to the receiver device. It must be noted that the channels programmed in the emulator are statistical representations of real-life propagation channels, which can be obtained either via channel measurement campaigns or using existing models in the literature.

Unlike existing commercial channel emulators, IKERLAN’s device is fully configurable and adjustable to specific user needs. Additional information and features of IKERLAN’s channel emulator can be found here.



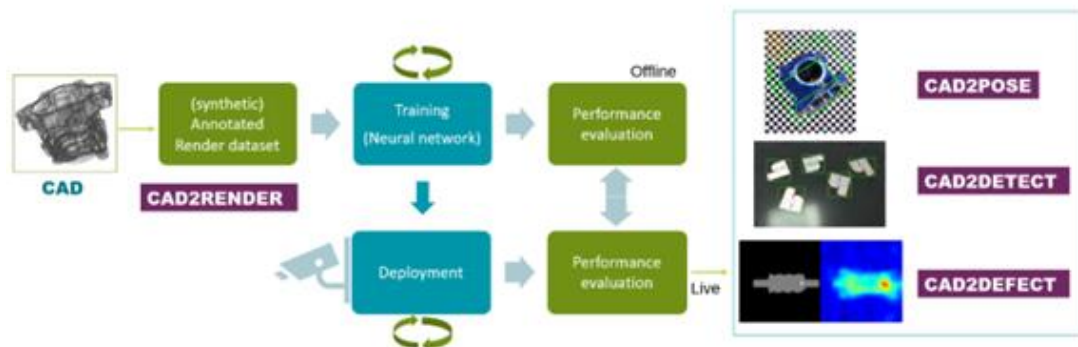
For more information, please contact:

earashi@ikerlan.es

BB8: Economic AI models for Industrial applications (CAD2DETECT, CAD2POSE, and CAD2DEFECT)

Industrial object detection, pose estimation and surface inspection are common industrial tasks. In Flanders Make we develop Artificial Intelligence (AI) techniques that can be trained fully using Synthetic data by rendering photorealistic images, with their embedded annotations, starting from Computer-Aided Design (CAD) models of these objects.

Three toolboxes have been developed, respectively, CAD2DETECT, CAD2POSE and CAD2DEFECT. These toolboxes are all end-to-end solutions for use in industrial environments to train and deploy, for instance, neural networks. The synthetic data generation is done using another Flanders toolbox called CAD2RENDER, which is a fully customisable dataset generation toolbox, which uses only a CAD file, information on the surface texture and domain knowledge of an object as input for the generation of huge, fully annotated datasets with depth maps. Altogether, they solve the need for large, annotated image datasets which are difficult to produce as it is hard, repetitive work to generate the annotations, prone to errors, if done using real images. The synthetic images can be generated in a fraction of the time compared to the traditional methods. The full flow for training and deploying these models is illustrated in the graph below.

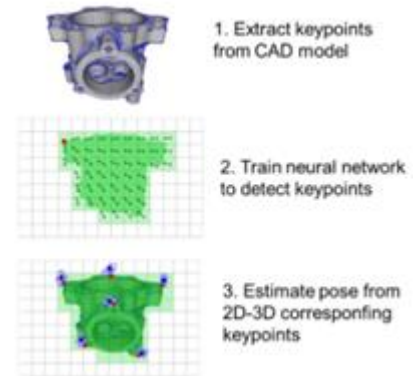
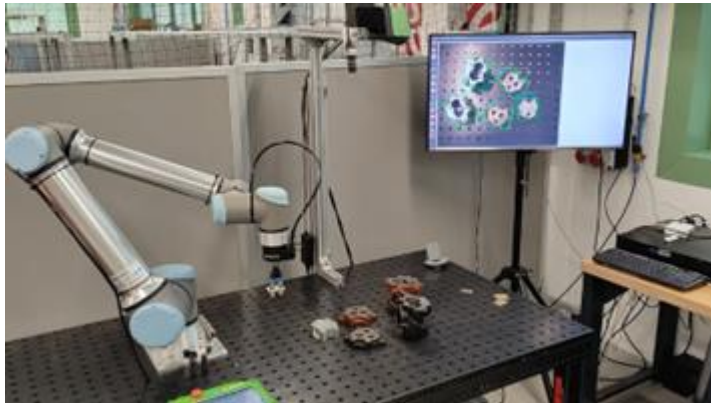


We can describe these 3 toolboxes in terms of the industrial applications in which these can be:

- CAD2DETECT is a tool allowing for fast and accurate object detection, identification and counting. A typical usage of this toolbox is sorting of various objects on a high-speed conveyor belt, based on the type of object. The tool uses a simple RGB camera for inference, it can potentially distinguish between hundreds of objects and deal with object occlusions.

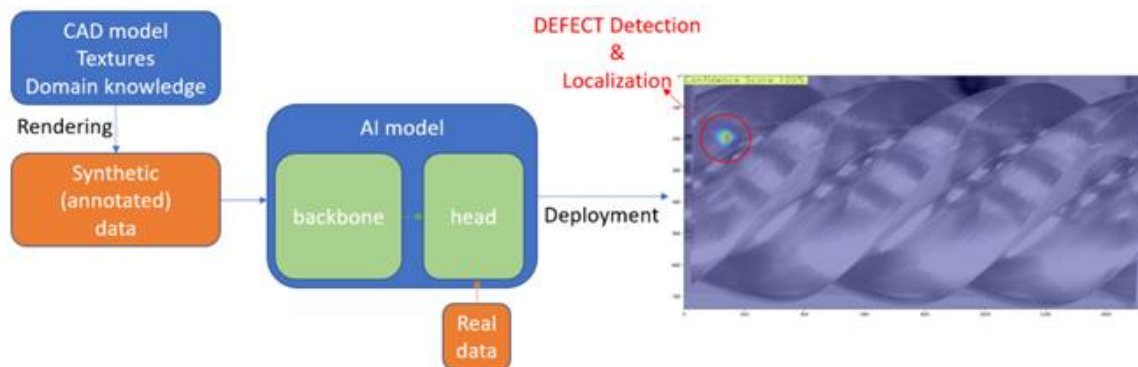


- CAD2POSE is a solution for 6DOF pose estimation tasks starting from a standard RGB camera, such as needed in a robotics bin-picking application. Highly robust against occlusion and harsh lighting conditions, it can accurately predict the pose of all kinds of objects, even if they are very flat, symmetrical,



or small. In combination with the CAD2DETECT toolbox, it is incredibly useful for managing mixed object streams in either stationary or dynamic sorting and robotic (bin) picking applications.

- The CAD2DEFECT solution is a highly accurate and fast surface defect detection tool for quality assurance. The initial state of the network is trained on a large synthetic dataset where virtual defects are present. The model is then further trained in a different way using a small dataset of real images containing no objects with defects, which are 99.9% of objects in the industry. This makes dataset generation very easy and efficient. This solution provides robust defect detection and furthermore, reduces the deployment time of such detection in an industrial setting significantly compared to other approaches.



For more information, please contact:

earashi@flandersmake.be

BB9: Operator Guidance Recommender

Generation of digital work instructions

The generation of work instructions which exploit digital content is already available in manufacturing, such as CAD files. The assembly sequence instructions are generated using a tool for automatically generating digital work instructions. The tool analyses the parts in the assembly and supports the user to automatically generate the assembly sequence, adding additional information such as assembly direction and text instructions. This information is used to generate animations. This way the instructions become clearer, while also dictating the appropriate way of assembling. The digital work instructions consist of two parts: (1) an animated image, in .gif format, that shows an animation of the assembly motion the operator should follow and (2) text instructions that explain the task and provide quantifiable technical details of the task, such as bolt torque. As the instructions are projected on a screen, it is important that the selected perspective of the animated image does not lead to ambiguity for the operator.



Figure 1: An operator using AR instruction to complete the task

(Credits: J Zegers, V Zogopoulos, D Verhees; Recommender systems for Personalized Work Instructions; Procedia CIRP, 2022)

The AR instructions are visualized using a dedicated headset that supports see-through projection of holograms (Microsoft HoloLens 2). This headset also supports user and environment-detecting technologies, such as hand tracking and spatial mapping, which are used to enrich the instructions with information on the part-picking position, which further supports the operator in picking the correct part, especially useful for inexperienced users.”

Guidance recommender system

Flanders Make has developed a guidance recommender system (RS), which selects the optimal work instructions for a given task and operator in real-time. There are many ways to represent instructional support: on-screen digital work instructions (DWI), Augmented Reality (AR)-based instructions, textual

instruction, etc. To assist an operator with the appropriate instructional medium and level of detail, the recommender system matches an operator’s proficiency, and a task’s requirement, with a level of instruction. The latter has the advantage that the recommended level of instruction is directly relatable to a skill-based operator proficiency metric.

The transition from paper-based to digital instructions that exploit the available content (e.g., 3D models of parts) allows fast and tailored operator instructions. Augmented Reality (AR) has arisen as a technology that may deliver instructions on the shopfloor in a fast and perceivable way, that maximizes the utilization of the existing digital content. The instructions are visualized in a 3D way, in the operators’ field of view, making it easier to understand the task. As different ways to support the operator emerge, a choice must be made on what support instruction to use. This is an adaptive process, where the amount of support an operator receives, reduces as the operator’s proficiency grows.

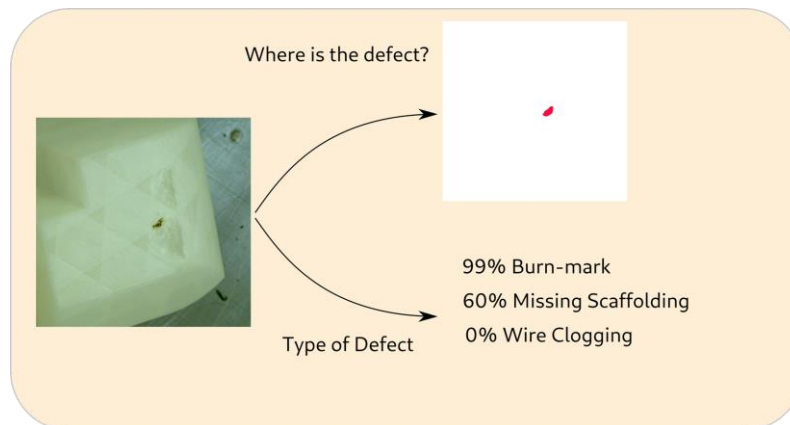
For more information, please contact:

earashi@flandersmake.be

BB10: Explainable AI

In typical production processes, there is an abundance of images related to good products. The industry has confronted a trend of product diversification due to changing customer demands, which leads to customized production. The operators need to adapt and learn continuously to the new products. The introduction of digital systems in manufacturing has increased the number of ways that assistant information reaches human operators in assembly workspaces. These digital system enables personalized training to the individual operator’s needs. These digital systems can adapt to different needs of support, based on the required level of detail and the experience of the operator. As the production environment becomes increasingly flexible and the tasks are changing at a faster pace, a more agile way of guidance allows maintaining productivity and quality, without introducing a higher stress level to the operator. However, only a few images are available of the different types of defects that might occur.

Tailored to this situation, Flanders Make has developed a toolbox capable of performing anomaly detection to make a fast decision between a defective product or not (important for rejection e.g., of a conveyor belt). In a second stage, a classification network is trained to decide which type of defect occurred, which could be interesting for control of the production machine. Next to which type of defect, we are also capable of pinpointing the location of the defect, making it easy for an operator to verify the decision of the algorithm.



The competitive advantage of Flanders Make in this field, is the fact that we not only use a wide range of state-of-the-art algorithms, but we also have vision experts in our group capable of designing an optimal inspection cell for a wide range of (surface) defects.

For more information, please contact:

earashi@flandersmake.be

BB11.1: Autonomy Toolbox – OASE

In order to create a working environment for the implementation of state estimation algorithms, like a Kalman filter, the **OASE** (Online Asynchronous State Estimator) Toolbox is developed at Flanders Make.

This C++ toolbox provides a fast and easy interface for the user. It can be used in C++, Python and MATLAB, and can be integrated with ROS for online applications. This toolbox is considered a valuable asset for estimation algorithm research as its modularized design enables an easy way to test different algorithm designs.

The estimation technology implemented in this toolbox is a Kalman filter based (extended Kalman filter, unscented Kalman filter, null-space Kalman filter). The main features of the toolbox can be summarized as follows:

- **Handle complex data scheme:** In most practical cases, different sensors have different sample rate, and their data will not be synchronized. Meanwhile, there might be a delay in the data due to data transmission or pre-processing (e.g., for camera images). The OASE toolbox handles the correct ordering of the data automatically. The users merely need to provide the measurements with the correct timestamp.
- **Low calculation time:** In this toolbox, the system model and observation functions, as well as the Jacobin matrix, are derived analytically using CasADi. Afterwards, C functions will be created to run the calculation. This ensures the main calculations of the filter are performed with very low calculation time, without the need for a user to manually (and error-prone) provide the Jacobian matrices. The measurement function of the system can be separated into multiple functions to modularize the implementation (normally one for each sensor), and the observation data for different observation functions can be fed to the filter separately.
- **Easy to use:** The toolbox is developed in C++. That way the best performance is guaranteed, and it can be integrated into embedded platforms. For fast prototyping, OASE also has Python and MATLAB interfaces.

Additional functionalities included in OASE are Outlier detection, Kalman smoothing, dual-mode parameter estimation

The toolbox includes a 'code generation' capability. Using this functionality, C++ code is exported in which all the functions used for state estimation are implemented. This code can then be used with the 'embedded' version of OASE, for which no CasADi-dependency exists anymore. Together with the python/MATLAB interface, this enables a user to develop the state estimator in a fast-prototyping environment, and once satisfied with the implementation, generate the C++ code required for implementation on the embedded/real-time target. Binaries for the following platforms exist:

- Windows: C++ and MATLAB interface
- Linux x64: C++, MATLAB and python interface
- Linux arm 64: C++ and python interface
- Windows, Linux x64, Linux arm 64, Linux -armv5-musl Linux -armv5 Linux -armv6-musl Linux -armv6 Linux -armv7 Linux -armv7a Linux -armv7l-musl Linux -mips Linux -mipsel Linux -ppc64le Linux -s390x Linux -x86: Embedded C++ interface without CasADi dependency

The toolbox is of interest to developers of (Kalman-filter) based state estimators, especially for online implementations with lots of different sensor inputs with measurements coming in at various frequencies and with delays.

For more information, please contact:

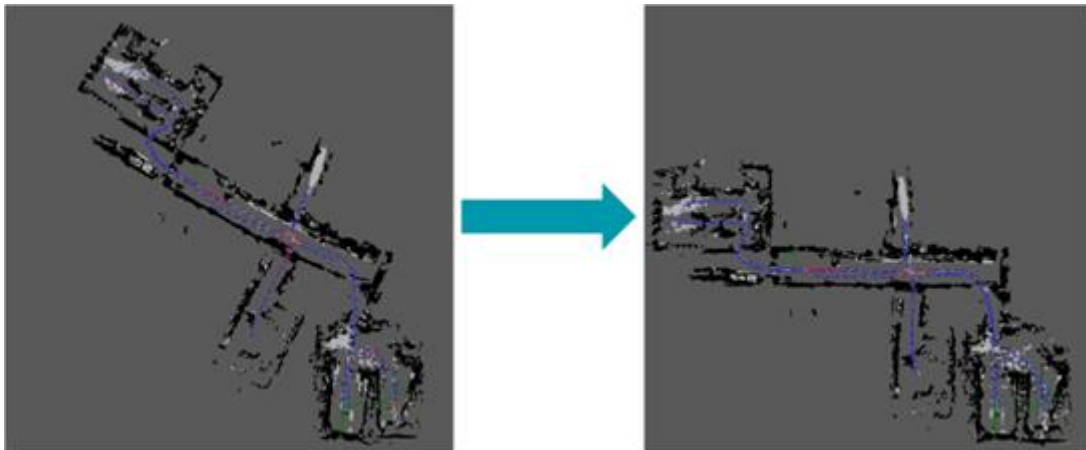
earashi@flandersmake.be

BB11.2: Autonomy Toolbox – FM-SLAM

The FM-SLAM system is a visual- or lidar-based SLAM that additionally supports the fusion of Ultra-Wideband, GPS, Aruco, WiFi or generic landmark measurements. This offers a high availability and high accuracy localization solution that requires minimal infrastructural changes. By integrating both relative measurements of the environment from cameras or LiDARs with absolute localization measurements, we increase the robustness, reliability and/or cost of localization. Which of these factors are improved, depends on the choice of sensor combinations.

FM-SLAM is based on the open-source SLAM framework RTAB-Map, which is modified to allow the additional fusion of the absolute localization measurements using graph-based optimization methods. The absolute localization measurements aid in achieving higher accuracy drift-free mapping and more robust loop-closure detection and relocalization. FM-SLAM is a stand-alone C++ library that runs on Linux-x64 platforms and offers a ROS/ROS2 interface.

As an example, in the figure below you can see on the left a map created purely camera-based, which contains a lot of drift. By adding only a few Aruco markers with known positions in the 50x30 meter environment, the drift in the map is removed.



The toolbox is of interest to developers/users of autonomous systems (e.g. mobile robots, drones) that want to move to SLAM-based localization for their systems, but cannot rely on a pure SLAM-based localization system.

For more information, please contact:

earashi@flandersmake.be

BB12: Mixed Reality for Operators

Collection of systems to provide ergonomic guidance during manufacturing or allow the operator to teach a robot in virtual reality.

This building block has been developed to provide operators with easy-to-use tools in order to achieve complex assembly tasks or robot-controlling tasks without the need for supervision or prior training. In order to do so, it leverages the power of Augmented Reality (AR), Virtual Reality (VR) and Mixed Reality (MR) to visually help and provide the Operator with the necessary information to perform the required tasks in real-time. In addition, the system keeps track of the task completion and is able to warn the operator if a mistake has been made.

The added value of this method is to avoid dividing the workflow into a training and a practice phase, allowing to bypass the training and directly jump into hands-on practice with the help of visual cues. Moreover, it allows untrained workers to fulfil critical tasks on the field and on the spot if required as well as monitor the correct completion of the tasks.

This technology is especially useful for companies that require operators to perform skilled manual tasks (like assembly or disassembly) or require operators to program a robot to perform such tasks.

The requirements for using such technology can range from a simple Mobile device (like an iPad in the case of AR) to VR headsets or XR technologies like Microsoft's HoloLens.

To drive VR headsets, a powerful desktop computer must be purchased.

Hereafter the sub-building blocks related to BB12

- **PROROB Framework**

Capturing of human motion using consumer-grade VR/MR hardware to program a robot.

- **DWI2PE (Digital Work Instruction to Production Employee)**

Application that can visualize the necessary instructions for an operator throughout each step of a discrete assembly/disassembly procedure. Can connect with advanced state estimators.

- **VR Training for Agricultural Machine**

VR driving training for Agricultural machines.

- **Mixed Reality visualization of Robot Forces**

Application that showcases an overlay in AR of the force exerted on a robot.

- **SmartFactory AR data visualization**

Visualization of Data of a smart assembly line.

ADDITIONAL RESOURCES

ROBOT AR Overlay: <https://www.youtube.com/watch?v=bjfbmogaFlg&t=1s>

Smart Factory: https://www.youtube.com/watch?v=DDozwa_9Ak

For more information, please contact:

earashi@flandersmake.be

BB13: Predictive Maintenance

The overall objective of the Monitoring Toolbox – Predictive Maintenance is to increase productivity through smart maintenance, reduce downtime and avoid catastrophic failures of machines, vehicles and production systems. It consists of an ecosystem of advanced signal processing and AI techniques for anomaly detection, fault diagnostics and prognostics, drivetrain modelling and cloud connectivity.

Through the usage of various sensing technologies, machine faults can be detected and predicted in bearings, gears, electric motors, clutches etc. Detection tools are available for bearing faults, gear faults, gear grinding faults, motor faults etc. Machine disturbances, such as gear noise in gearboxes, are mitigated through robust diagnostic and prognostic tools. These AI tools and models enable pre-emptive maintenance through in-time replacement of discrete components.

In a regular state, a machine exhibits a very specific vibration pattern/identity. If just a tiny fault is present, this vibration pattern changes. Sensors measure this vibration pattern up to high frequencies. The system filters out unwanted noise which is present in an industrial environment.

The validated Flanders Make advanced methodology highlights the modulation which exists in the spectrum and provides the user with accurate information in order to detect the fault early and accurately. Advanced algorithms continuously compare the vibration pattern from the machine when it was in perfect order (the reference model). These algorithms have an open character so they can be further modified and optimized on the application-specific requirements.

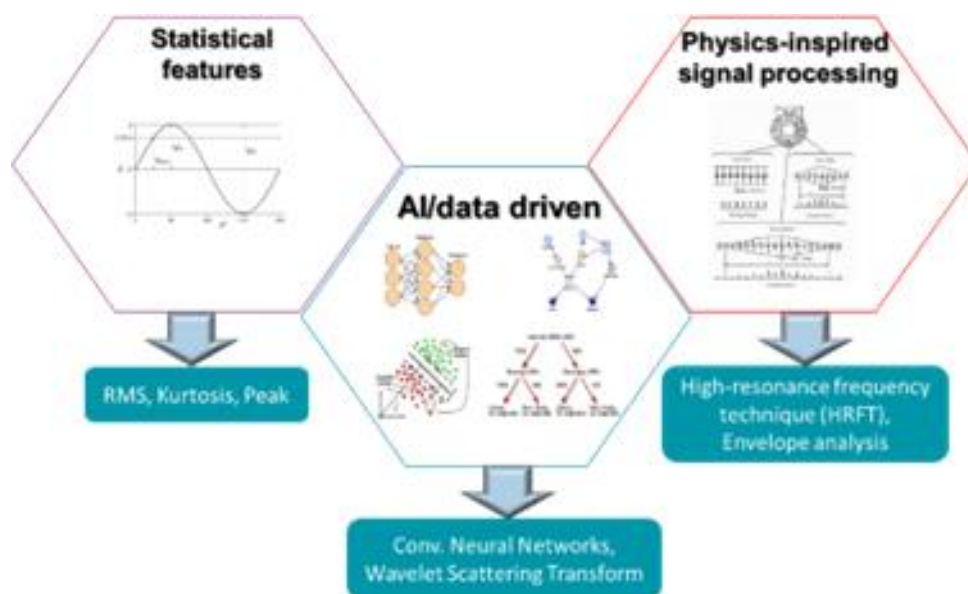


Figure: Machine fault detection and diagnostic methods.

EXAMPLE CASES

- Robust and early detection and diagnostic of bearing and gear faults:
 - *Issue*: gear noise effects typically mask the effects of incipient bearing faults in gearboxes.
 - *Solution*: automated, computationally efficient, robust, and open algorithms for early fault detection running with embedded low-cost hardware.
- Accurate prognostic methods for remaining useful life prediction of bearings with limited industrial data:
 - *Issue*: limited amount of data available of failing machine components hampering the applicability of traditional AI tools.
 - *Solution*: hybrid remaining useful life methods.
- IoT architecture design for cloud-connected machine monitoring:
 - efficient local data reduction and transfer and cloud connectivity
 - transfer of classification models for easy deployment
 - efficient edge processing and metadata management

LINKS TO DEMO VIDEOS:

- Condition Monitoring: <https://www.youtube.com/watch?v=xhKTDnxrnKs>
- Smart Maintenance : <https://www.youtube.com/watch?v=dTBxTV2yfGA>
- Data-efficient AI and digital-twin technologies for fault detection: <https://www.youtube.com/watch?v=JbDNpk-lwr8>
- <https://www.youtube.com/watch?v=nWcyVUaz94I&t=1s>

For more information, please contact:

earashi@flandersmake.be

BB14: Data Operationalization Methodologies

This Building Block could be described as a set of tools to support the process of digitalization in production equipment and processes, ranging from identifying the goals of digital transformation and aligning them with the company's strategic vision, to continuously collect data and understanding the behaviour of the main variables involved. It was created in order to create procedures to support the process of digitalization and data operationalization in production equipment, being this a process that covers several areas of knowledge - IT, OT, Automation, etc.- and which can imply a major change, both in terms of the necessary skills and in terms of the company's mindset, this methodology was created in order to contribute to a change as smooth as possible.

The Building Block has the following features in order to support data operationalization: Goals Mapping, Data Sources Identification and Classification, Fundamental Architecture, Data Acquisition Implementation, Harvesting and Usefulness, and Analytics Automation, and at the time of the development of this methodology, no other solution was found that would support the overcoming of the same challenges and that would provide a set of tools with the same objectives.

This Building Block mainly fits companies interested in the digital transformation of their products or in introducing technological solutions that generate data.

A typical use-case of the BB would be a production machines manufacturer, interested in transforming its product towards digitalization, by introducing IT and OT layers for data acquisition, aggregation/processing, visualization and analytics.

However, a **requirement for this Building Block** is that SMEs must ensure they understand the change in mindset adjacent to digital transformation and the financial capacity to acquire hardware and software that in the Building Block implementation may be identified as relevant to the context, whether for data acquisition, aggregation/processing or storage.

For more information, please contact:

Marco Rodrigues - mrodrigues@inegi.up.pt

BB15: ADAPT: Context-Aware System for Collaboration Between Multiple Agents

The framework ADAPT, performs the automatic diagnosis of industrial automated processes (machines and operators). By interpreting, from process and operator data, the context and the fulfilment of procedures associated with tasks or operations: (i) verification of correct task performing with respect to a predefined ideal procedure and worker experience; (ii) novice operator training and guidance, increasing awareness, comfort, trust, skills and safety (physical and social) of workers.

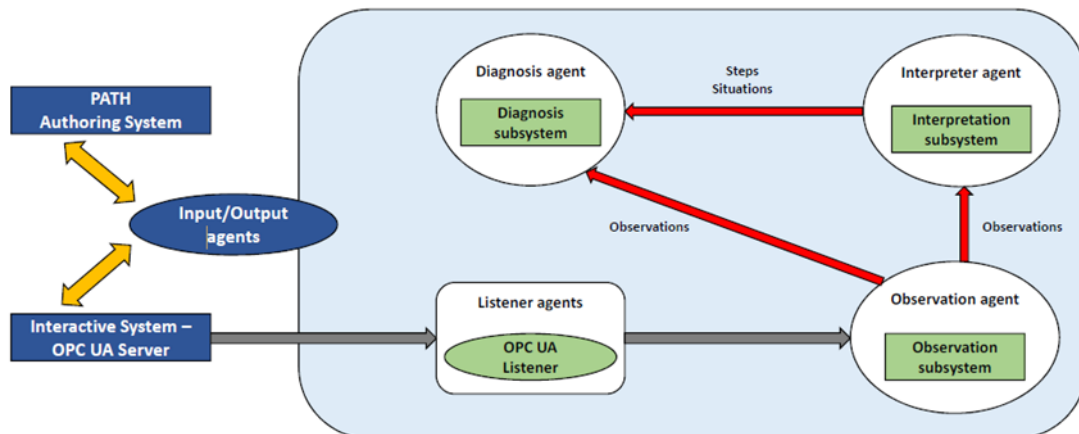


Fig. 1: Interaction between the ADAPT agents.

The basis is a domain-independent metamodel inspired by the cognitive process that real domain experts or tutors (e.g., in educational scenarios) carry out while supervising or tutoring a learner during a process: experts first perceive facts or observations happening in the environment. Then, they interpret those observations in order to identify actions (i.e., they unconsciously assign meaning to their observations in the context of the domain) being carried out, and once they have processed this information, they make a diagnosis, which involves detecting and/or correcting mistakes.

The metamodel is divided into three subsystems (a) Observation, (b) Interpretation and (c) Diagnosis subsystems.

Observation level: This level contains the necessary elements for specifying the observable facts that are interesting from an educational or process diagnosis point of view.

Interpretation level: Interpretation level describes generically how to recognize ISs with such accuracy that the diagnosis subsystem is able to determine whether the actions are correct or incorrect and its reasons. To that aim, it is essential to know the context where the actions are happening.

Diagnosis level: The objective of this level is to manage the elements that will allow an appropriate diagnosis of the activity to be generated. ADAPT provides the educational or process evaluation components of the built system with real-time diagnostic results or final evaluation results as needed. The diagnostic results contain information at different levels: the correctness of situations, the correctness of every step within each situation and other information such satisfied and non-satisfied conditions within the steps.

The framework ADAPT holds the above mentioned three subsystems that will jointly contribute towards the implementation of the context aware system.

For more information, please contact:

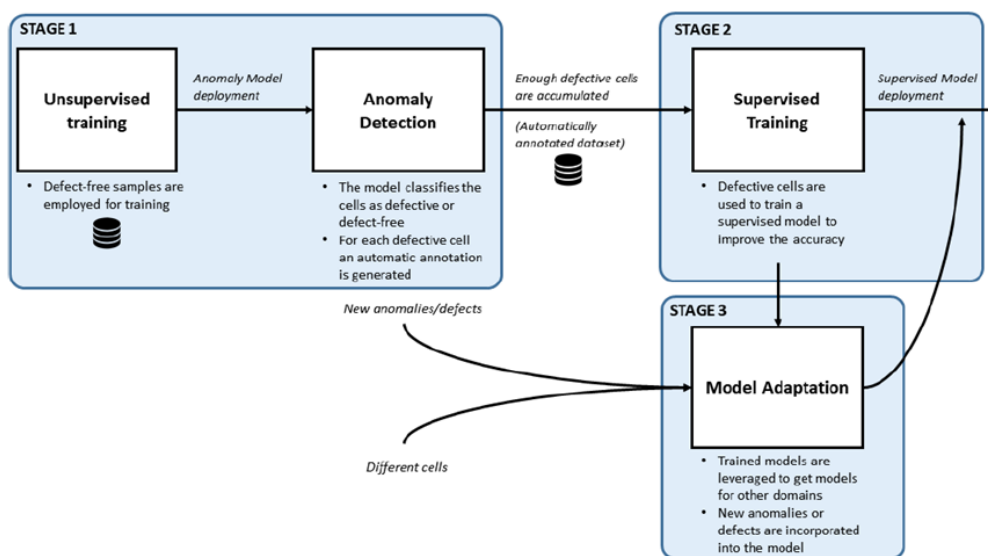
Luka Eciolaza – leciolaza@mondragon.edu

BB16: Deep Learning based Industrial Quality Inspection Methodology

Quality inspection applications in industry are required to move towards a zero-defect manufacturing scenario, with non-destructive inspection and traceability of 100% of produced parts. Developing robust fault detection and classification models from the start-up of the lines is challenging due to the difficulty in getting enough representative samples of the faulty patterns and the need to manually label them.

Automatic Quality inspection of industrial parts is crucial. However, the proposed solutions to this day are not as generalizable to different scenarios as one might wish as they heavily rely on case and situation specific features in order to design the inspection system.

This building block provides access to a Deep Learning based methodology for the development of robust and flexible industrial inspection systems.



This methodology has the following steps:

Stage 1 - Anomaly detection: In the first stage of the set-up of a new production line, an anomaly detection approach would be used. By training a network using only non-defective parts, the products that are out of normality, i.e. anomalous or defective, would be identified. In addition to classifying them, the defective areas within the product would also be marked for inspection, i.e. defect segmentation. In this way, it would not be necessary to wait for having enough defective samples for training, and it would be possible to start detecting defects from the beginning.

Stage 2 - Supervised training: During the lifetime of the production line, it will generate defective products which will be automatically identified and annotated at pixel level by the model from the first stage. Once a handful of these defective samples are accumulated, they will be used to train a second model in a supervised manner and using methods that require little data for training. This second model will be trained specifically to search for concrete defects reaching higher accuracy rates than the previous model in detection.

Stage 3 - Model adaptation: In a production system, there may be features that are not common and rarely appear during production. It could also happen, that similar inspection scenarios could take advantage of existing models. For this case, the methodology proposes two DL based techniques called Few-shot learning and Transfer Learning, which take advantage of the previously trained models to obtain new models that will be adapted to work on the new line. Using already trained models as the starting point alleviates the need for defective data which accelerates the deployment of the new line.

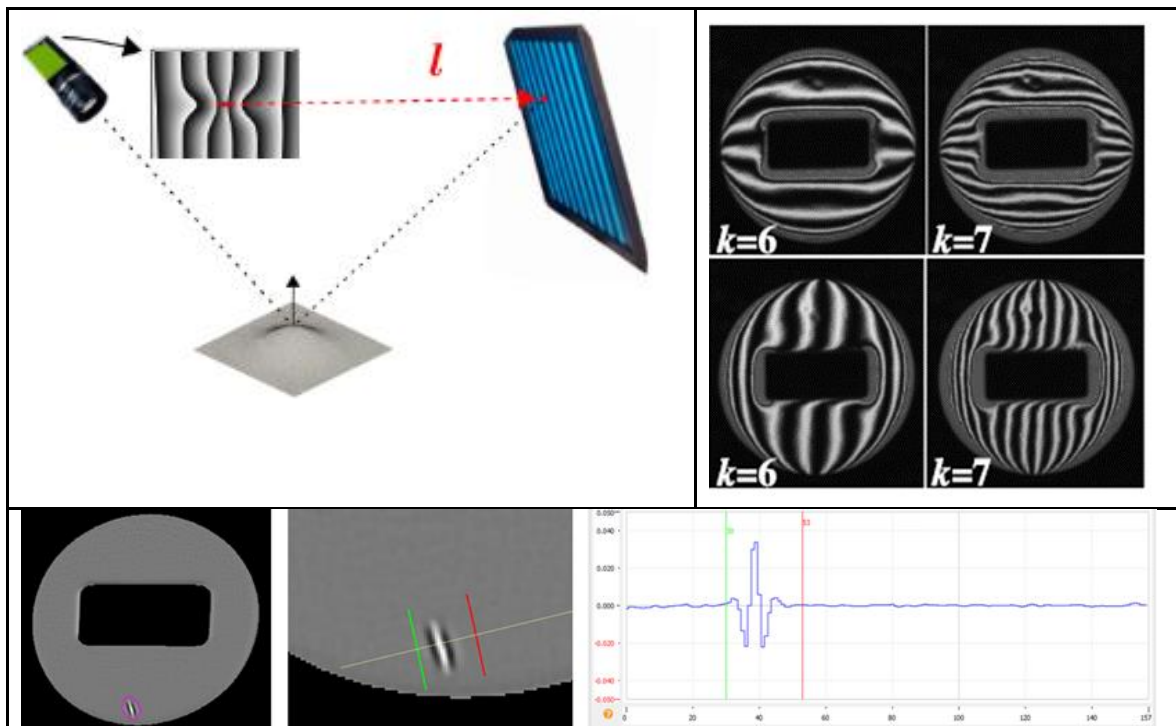
For more information, please contact:

Luka Eciolaza – leciolaza@mondragon.edu

BB17: Deflectometry for Surface Quality Inspection for Glossy or Shiny Finish

Deflectometric techniques provide abundant information useful for aesthetic defect inspection in specular and glossy/shiny surfaces. A series of light patterns is observed indirectly through their reflection on the surface under inspection, and different geometrical or texture information about the surface can be extracted.

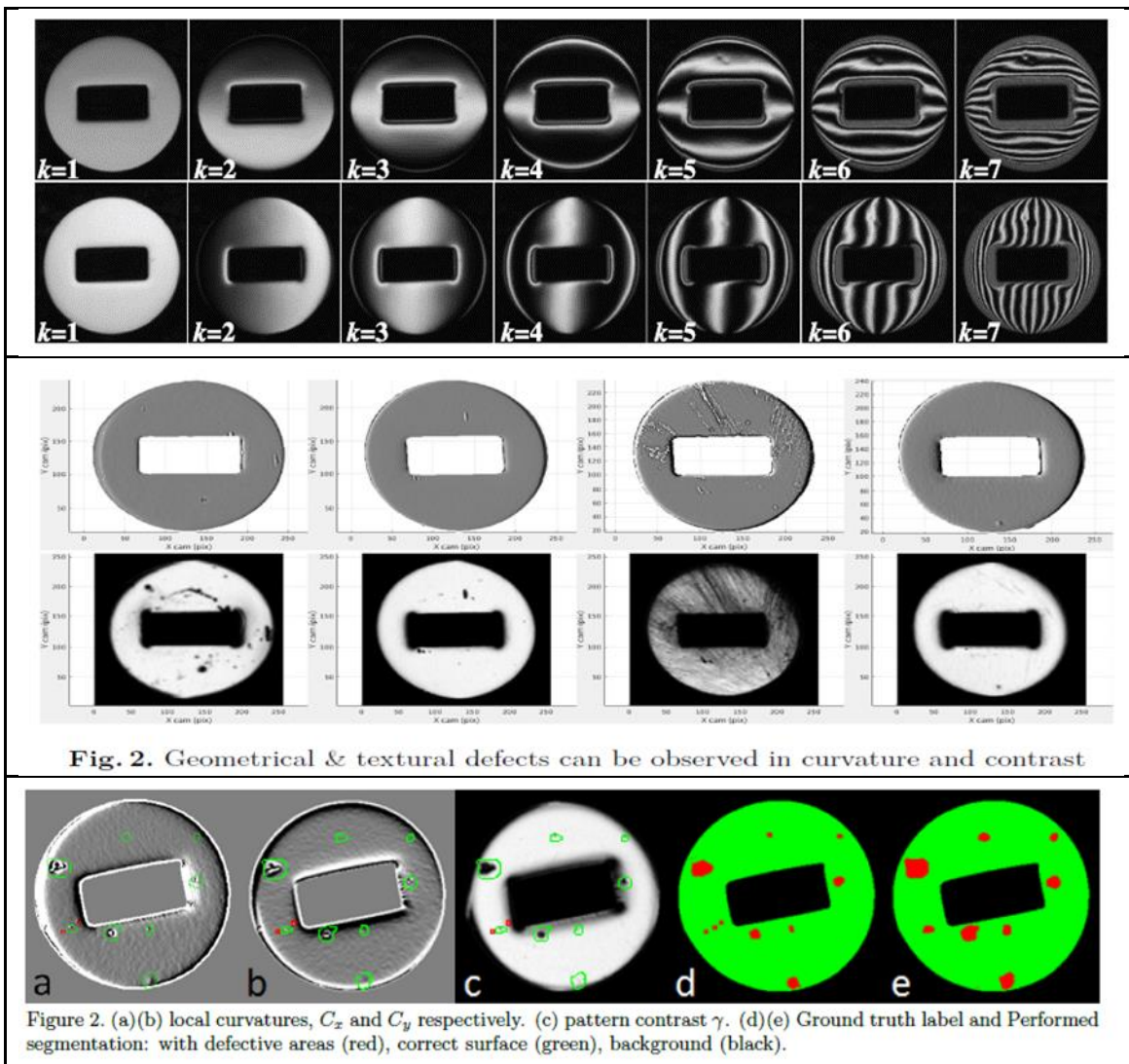
A typical deflectometric system consists of a camera, or several cameras, focused on the surface under inspection and an LCD screen displaying a series of spatially coded patterns placed nearby, such that the camera observes such reference structure from its reflection on the surface.



This technique has been applied in different industrial scenarios, obtaining qualitative results for different type defect detection, or quantitative results with absolute measurements.

This technology can also serve to perform a surface inspection in big size parts, within a robotic cell.

Defect/Anomaly detection based on deep learning can also be included in order to accelerate the inspection time and robustness.



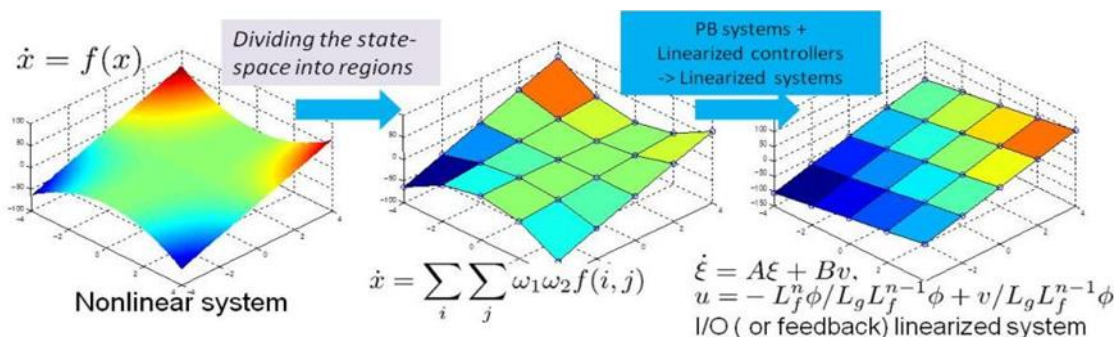
This technology will be available in the project, taking into account that it will have to be adapted to address correctly the particular needs of each use-case or challenge. Acquisition set-up optimization must be realized depending on part geometry variability (light patterns, part orientations, capture time, etc.)

For more information, please contact:

Luka Eciolaza – leciolaza@mondragon.edu

BB18: Fuzzy Logic-based Modelling

Fuzzy Logic modelling capability in order to implement a hybrid AI system based on knowledge base, sensory input and human expertise. This methodology will enable a linguistic rule-based plant model explainable in its nature, and will be used as a decision support system.



This technology will enable the controller design including (a) expert rules, obtained from operator knowledge or data, (b) controller design based on mathematical models, or (c) system identification based on I/O data and controller design.

This technology can also serve to implement a Feedback error learning (FEL) control scheme. FEL is applied as an on-line sequential learning strategy of inverse dynamics, that will be used as a feedforward command. It sequentially acquires a pseudo-inverse model of a plant through feedback control actions.

For more information, please contact:

Luka Eciolaza – leciolaza@mondragon.edu

BB19: LeanDfX Framework

This Building Block consists of a lean-based framework (methodology + tool) developed by INEGI, devoted to Design Performance assessment, for either PRODUCTS / SYSTEMS namely complex products/systems in multiple dimensions "X" (multidimensional design performance assessment), based on life cycle mindset. Evaluate products and systems performance in the two components (effectiveness and efficiency) mapping the requirements/specification accomplishment and also inefficiency (over-engineering of design). Original Scorecards for performance mapping and related Design Parameters (Design KPIs). It was developed after the need for processing multiple data and multiple dimensions (design iterations, specification iterations, KPIs, etc.) was identified.

The function of the Building Block is to Design Performance assessments, for either PRODUCTS / SYSTEMS namely complex products/systems in multiple dimensions "X" (multidimensional design performance assessment), based on a life cycle mindset.

The LeanDfX methodology is an innovative form to assess complex products and systems performance in a multi-dimensional way, Lean Thinking-based, Original Scorecards for multiple "X" disciplines, therefore, no other tool/methodology was identified with the same goal.

Products, Machines, and Systems development companies could be interested in this BB, which want to measure and track design versions and status of the design (effectiveness regarding objectives-requirements-specifications and efficiency - over-engineering). Mapping trade-offs in multiple dimensions of the design (Design for-Assembly, Manufacturing, Cost, Environment, Reliability, Safety, Circularity, Logistics, etc. etc.).

A typical use case of the Building Block would be Advanced Design Support to Products/Machines/Systems to development and design teams and companies.

As a requirement for the usage of the BB, SMEs must ensure good product structure information, vision to evolve their design process and adequate matured Management System (for instance that already use approaches such Lean Thinking) so that they can take full advantage of LeanDfX Tool and Methodology.

For more information, please contact:

Marco Rodrigues - mrodrigues@inegi.up.pt

BB20: MSM (Multi-Layer Stream Mapping)

This BB consists of a lean-based framework (methodology + tool) developed by INEGI, devoted to systems/processes efficiency assessment, mapping hotspots of inefficiency and relation to waste in multi-dimensional variables and groups of KPIs. Original Scorecards for efficiency mapping. Cost graphs disaggregating Non-value added costs from added costs for a given product, and it was developed so that it could process data related to the KPIs and display the results in a scorecard original format in multiple dimensions (time-based periods, KPIs, production orders/products IDs, etc.). Its main features are Mapping Efficiency (Resources, Operational, etc.) in multiple KPIs, system complexity, Costs Value Added and Non-Value Added.

The MSM methodology is an innovative form to map efficiency in a multi-dimensional way, Lean Thinking based, Original Scorecards, VA/NVA cost disaggregation and data monitoring (it is ranked in European Commission Innovation Radar).

Companies interested in the digital transformation of their products or in introducing technological solutions that generate data could be interested in this BB.

A typical use case of this BB would be Production Systems Efficiency Assessment, General Systems Assessment. Resource Efficiency and Operational Efficiency, Efficiency Monitoring, Costs Assessment (VA and NVA).

For this Building Block implementation, SMEs must ensure that they have enough digitalization of their processes and mature Management System (for instance that values approaches such Lean Manufacturing) so that it can take full advantage of MSM Tool and Methodology.

More information about the BB: <https://www.innoradar.eu/innovation/36437>

For more information, please contact:

Marco Rodrigues - mrodrigues@inegi.up.pt

BB21: Skill-based AI enabled Robot Programming Framework

SHORT DESCRIPTION

An AI-enabled human-centered architecture that allows operators to be supported in their work by skill-based programmed robots or cobots, smart sensing systems and intuitive human interaction tools.

CONTEXT

Flanders Make has developed an extension to the [SkiROS2](#) Skill-based robot control platform, to create a more generic human-centered operator support architecture for assembly work cells. Therefore, multiple components related to human-machine interaction have been added such as a smart sensor system, work instruction platforms and a central knowledge base. To make the human-machine interaction more intuitive, AI components were added that enable the operator to control the system using natural language, to demand quality checks of his work or to request task-related knowledge or support.

FEATURES

The architecture is centered around the SkiROS2 robotics framework and therefore inherits all the features related to skill-based programming: task planning, motion planning, skill libraries, etc. Apart from this, a centralized knowledge base is added to contain all the relevant information about the assembly work cell. The added speech interface recognizes intents from natural language and routes these intents to the active components in the framework: this could be skill/task request to the robot, a need for a digital instruction or a general request for information to the knowledge base. In the near future, this will be extended with an AI-based vision component that keeps track of the assembly state and can perform (visual) quality checks on demand. The framework is continuously improved to optimize existing functionalities and integrate other components that are relevant for operators.

DIFFERENCE WITH EXISTING SOLUTIONS

There is no single framework that combines all these functionalities in one solution. Integrators can develop custom tools to connect components, but it will be more expensive and difficult to maintain. As this framework is hardware agnostic, companies can easily interface existing infrastructure. Operators without programming skills are able to retrain the system for a new situation, using reusable skills.

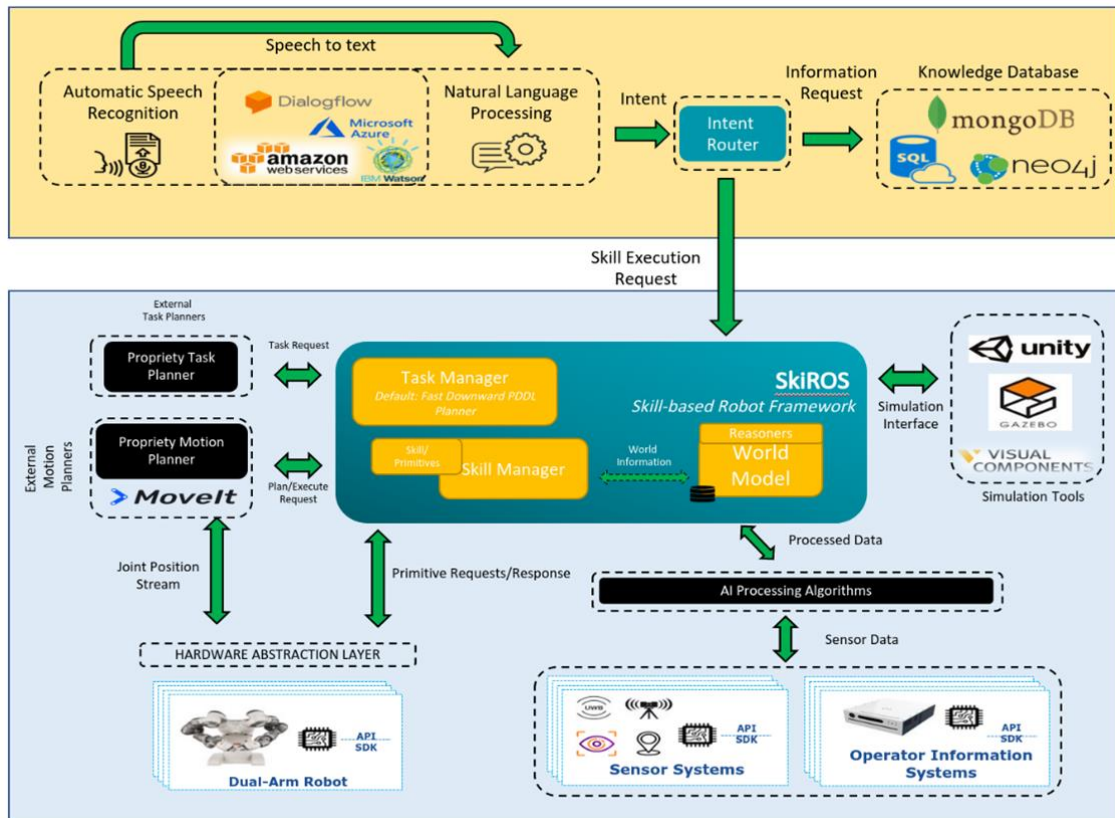
WHO MIGHT BE INTERESTED / TYPICAL USE CASE

This framework is highly relevant for companies that deal with complex manual work (e.g. assembly, packaging) and a large or changing product portfolio or workforce. This framework will result in increased quality and productivity, by providing better support (on demand).

HARDWARE REQUIREMENTS

The specified framework is modular and hardware agnostic. In its simplest form, only a computer that can run ROS2 is needed to host the software and the knowledge base. Depending on the needs of the customer,

different robots, cobots, sensors or information systems can be plugged into the framework. If natural language interaction is desired, a microphone should be connected to the PC.



ADDITIONAL RESOURCES

- <https://www.youtube.com/watch?v=Vdxq8yC8LIA>
- <https://github.com/RVMI/skiros2>

For more information, please contact:
earashi@flandersmake.be

BB22: Follow-Me principle - SmartHandler

INTRODUCTION

This building block is about a control principle and technology objects to improve the ergonomics and operational efficiency of manual cranes.

PROBLEM

A wide variety of cranes are used in the industry, ranging from motorized cranes which are usually utilized for large loads and large operational distances, to completely manual/passive cranes for smaller loads and relatively shorter distances. The latter only supports the payload in vertical directions, and operators still have to manually transfer the payload in the horizontal direction. As the operator pushes or pulls the payload in the desired direction of motion, tension is created on the cable/chain where the payload is hanging, which in turn moves the moving part of the crane (i.e. overhead bridge and/or hoist with the trolley) in the same direction. This motion demands excessive force from the operator, not only because of the inertia of the load but also because of the inertia of the mobile parts of the crane. Similar excessive forces are experienced by the operator when stopping. What is more, because mobile parts lag behind the payload during the travel, there is always a swing action at the stop position which causes additional effort/time to stabilize. As a result, excessive forces experienced by the operators cause ergonomics issues, and the time taken to stabilize the load causes additional operation time. The Follow-Me principle focuses on compensating the forces that are required to move the inertia of the mobile parts of the crane. The applied principle also enhances the stability of the system. Therefore, there are significant improvements in ergonomics and operational efficiency.

SYSTEM DESCRIPTION

Figure 1 shows the Follow-Me principle for a single-axis crane with a hoist. If an operator moves the load, the angle between the hoist chain/cable (α) will be non-zero. By using this angle as an input to a proportional-derivative feedback control loop (PD-controller), the hoist can be actuated to compensate for its inertia. The amount of actuation can be changed by tuning the PD-controller gains.

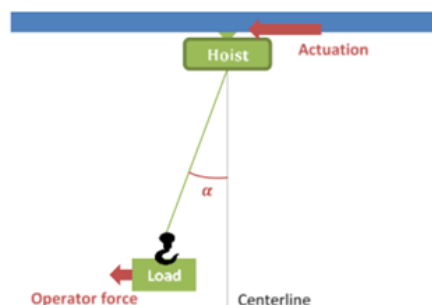


Figure1: Follow-Me principle: the inertia of the hoist is compensated by actuating it using the angle feedback between the chain/cable and centreline of the hoist (α).

The principle can be applied to 1-axis gantry cranes, jib cranes and overhead cranes. Motors are added to assist the motion in desired axes, a sensor is added to measure the cable/chain angle and a control system is added to run the control logic. Figure 2 shows a control architecture implementation for a 2-axis overhead crane where the hoist and trolley (X-axis) are actuated with one motor, and the overhead bridge (Y-axis) is actuated with 2 motors at each side of the bridge.

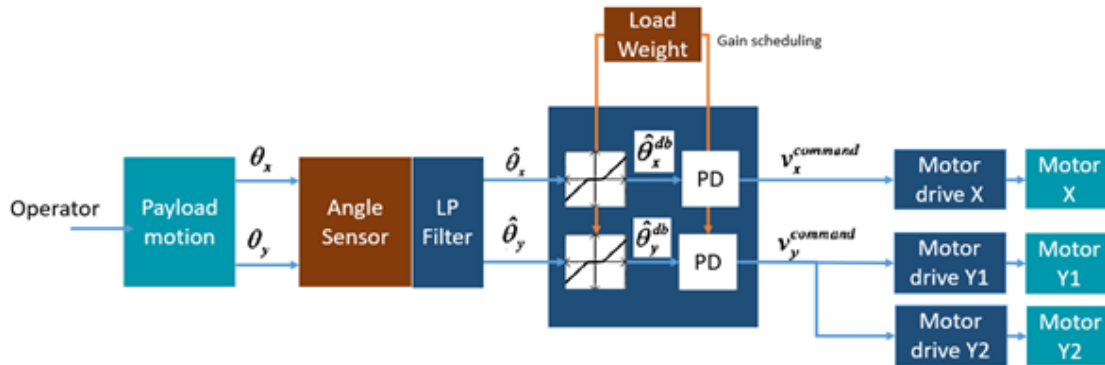


Figure 2: Follow Me control architecture for an overhead crane.

A load cell can be added to measure the payload weight and change PD parameters accordingly. This helps to improve the system response with respect to varying payloads which in turn results in a better user experience and operator acceptability.

DIFFERENCE WITH EXISTING SOLUTIONS

The crane systems equipped with Follow-Me combine the comfort of motorized cranes with the agility of manual cranes and It brings additional benefits with respect to ergonomics and operational efficiency.

WHO MIGHT BE INTERESTED / TYPICAL USE CASE?

Those who suffer from ergonomic issues with manual cranes and/or those who want to have a more stable and faster operation.

ADDITIONAL RESOURCES:

- [Concept](#)
- [2 axis crane without Follow-me demo](#)
- [2 axis crane with Follow-me demo](#)

For more information, please contact:

earashi@flandersmake.be



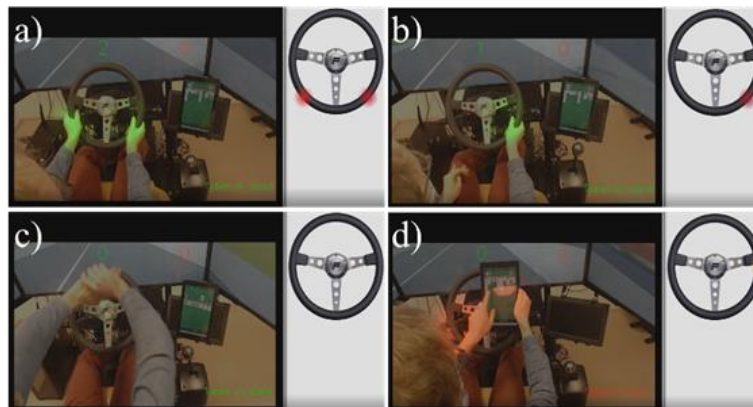
BB23: Manual Task Recognition

Building block “Manual Task Recognition” can identify a known manual task in real-time.

This block was initially developed for the European project “HADRIAN” to improve the comfort and safety of drivers of autonomous vehicles. Its aim was to identify whether the hands of drivers were holding the steering wheel or not.

A camera films the expected hands’ location, and an artificial neural network identifies in real time the executed task. The used camera can be either RGB or infrared to allow use in dark environments with infrared lighting. In order to train the artificial neural network, a big database of images, taken while performing the expected tasks, must be acquired and annotated by a third party. A GPU is required to run the artificial neural network. The size of the database may be reduced if using transfer learning from a previously pre-trained model. In inference mode, the system tracks the hands and does not keep any images in the memory. In learning mode, the camera can be placed so that faces are not visible in the recorded images. An automatic face blurring block can also be added to the recording system so that the stored images would not contain any facial information.

In the following figure, four cases of hand detection are presented.



More details on the developed system are given in the following video (NB: for EARASHI project, the part of the system using grip sensors is not proposed):

<https://www.youtube.com/watch?v=qfYOM4sdWr4>

This building block can be used to verify whether a workstation is well adapted to the operator or not. For example, if hands are not detected at the expected positions, it can allow to identify that an adaptation of the workstation must be done to help the operator keep his/her hands in the right position during hours. It also can allow to improve safety by interrupting the robot’s movement if the operator is not executing the good task at the right moment.

This building block can be used in situations where there is a will to improve physical working conditions and the safety of operators.

For more information, please contact:

Claire Guyon-Gardeux - claire.gardeux@cea.fr