# AUTOMATING AUTOMATION: MASTER MENTORING PROCESS

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***ABSTRACT***

*This paper describes an innovative computer system framework supporting robot automation programming, by a gesture controlled "show and tell" process, whereby human experts describe their goals of a process to be learned, and demonstrate via positional sensors(such as Microsoft Kinect or Leap Motion) the actions necessary to achieve those goals. These inputs are collected and optimized by the robot mentoring process, interpreted back to the human expert for confirmation feedback and/or subsequent fine tuning. This framework, is a pedagogical model, modelled on a professional human process needed to mentor others. We have applied this concept in an innovative way to mentor robots with gesture control and machine learning.*

***KEYWORDS***

*AI, Automation; Robotics; Deep Learning; Really Useful Machine Learning.*

## 1. INTRODUCTION

As technology advances and novel tools in AI and IoT emerge, paradigm shifts in industrial settings becomes more and more imperative. Accelerating the manufacturing process has been supported via different practices such as rapid prototyping technology as well as facilitated setup and intuitive programming interface for conventional manufacturing process. Offline programming of the robots within an intuitive 3D modeling and simulation environment has attracted lots of attentions in the recent decade as a solution to speed up the "order-to-delivery" process [1]. In this regard, this paper proposes an organized procedure for a smart master mentoring process aiming at "automating the automation" using AI tools such as Deep Learning and rule extraction methods such as Really Useful Machine Learning (RUML$^{SM}$) [2] a patent pending process [3].

Heuristic motion training approaches such as robot learning by demonstration and interactive human robot interface for path planning is one of the research areas that has properly been investigated before[4], [5].To this end, different conventional tools such as Deep Learning [6], [7],reinforcement learning [8], and hidden Markov model[9], and probabilistic segmentation of movement primitives [10]can be used. Moreover, heuristic mathematical models and methodologies in probabilistic filtering and inference such as feedback-based information roadmap[11], filtering in presence of partial observation [12],[13],and adaptive uncertainty propagation for coupled multidisciplinary systems [14]have the potential to improve the robustness of the proposed framework against the uncertainties in dynamical environment.

Such motion training approaches can potentially profit the automation industry. However, a holistic paradigm shift in automation industry in order to expedite the order-to-delivery process is

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a chain yet with several lost rings that need to be addressed. The new paradigm must provide solutions for different domains, applications, goals and tasks. It also needs to provide the rationalization behind the provided solutions such that one can evaluate its the efficiency and effectiveness of the solutions. Such a rationalization can extend the applicability of the gained expertise into new domains by extrapolating the rationale to similar tasks in a new domain. The master mentoring process not only provides a step-by-step training framework from beginner to expert stages but also incorporates new approaches such as learning by demonstration and smart motion planning to facilitate the programming of the robots. Furthermore, it utilizes RUML$^{SM}$ Learning [3] to rationalize the acquired knowledge. The proposed training framework, is a pedagogical model, modelled on a professional human process needed to mentor others. We have applied this concept in an innovative way to mentor robots with gesture control and machine learning.

## 2. METHOD

Figure 1 illustrates show & tell process for a master mentoring robot training process; the description is of the major embodiments in the figure. First an abstract / generic description of the stages is described, then an example is given as to its application to the "Show and Tell Master Mentoring Robot Training Process" specifics.

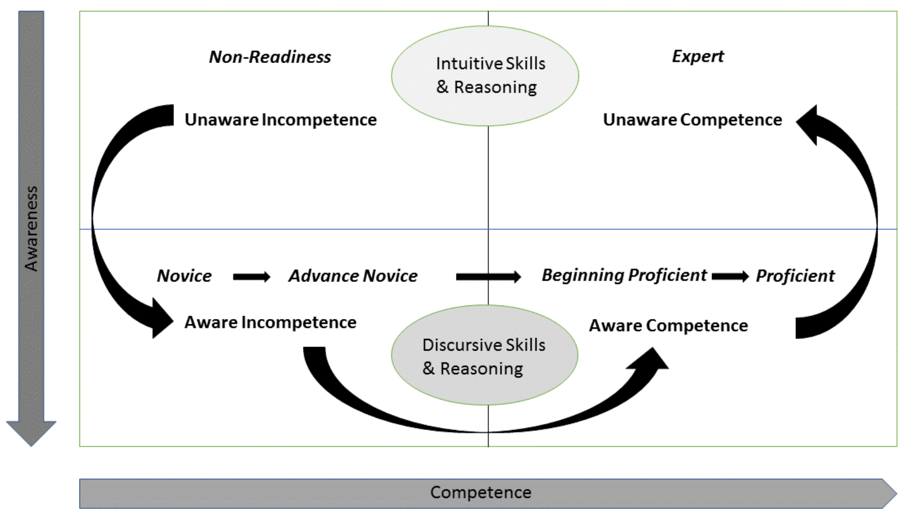


Figure 1. Master Mentoring Process is a Show & Tell Process proposed in this paper to automate the automation and to train the robots.

See Figure 2 for illustration example of non-readiness stage, where we are at an unaware incompetence situation. The human expert user (hereafter referred to as the Trainer) specifies the domain of the learning application and the goals of the process being trained. For example: Domain - Six Axis Robot Pick and Place; Goal -To Pick from Conveyor a Specified Tool and Place it into a Storage Container. The Robot Mentoring system has software to recognize the match of the Domain to an Application Library set. In addition, the specification of the Goal first seeks to determine if a matching Application definition pre-exists to be used or sets up a new Application definition based on either a) Drop down Menu driven by the context of the Domain/Application specification and Goals, or b) Natural Language Processing (NLP) parsing of the Domain/Application specification and Goals.

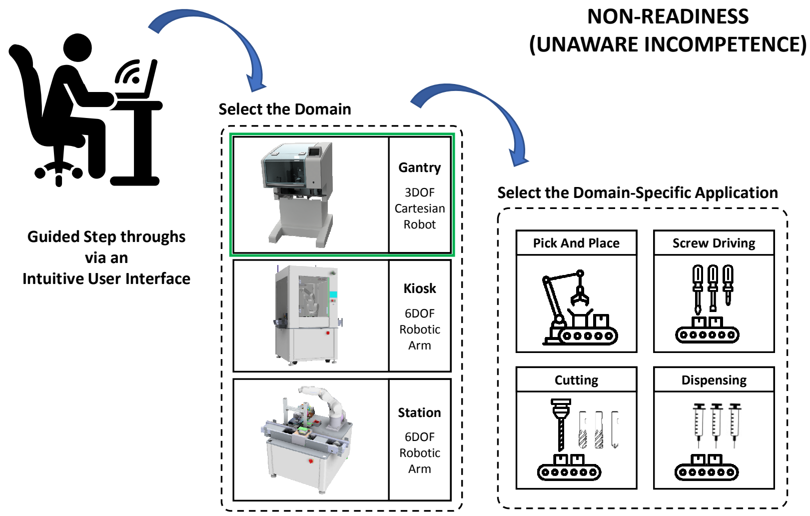


Figure 2. An intuitive user interface is provided to select the domain, application and finally define the goals.

Figure 3 for illustration example for novice stage, where we are at an aware incompetence situation. Basic gesture learning of objects and actions is useful for process tasks that have many alternative options for physical movement, e.g., the movement of a Robotic Arm (kinematics) for point A to point B in a 3D space. Motion capture technology, such as provided by Position Sensors, Proprioception (Stereoscopic and Depth detection by visual and/or ultrasonic) Sensors, can be used. The Trainer performs a motion, this is captured in a 3D Simulation software package. The Simulation is played back to the Trainer for fine tuning. For object assignment tasks the Motion capture technology can be used to point at Objects, and assign them labels as appropriate to the Application specification, whereas an application is referred to the main task of the automation goal such as Pick and Place, Screw driving, Cutting, Dispensing, etc.For instance, one can consider pointing at a Storage container for a Place process to deliver a Specified tool to in a Pick and Place Application specification.

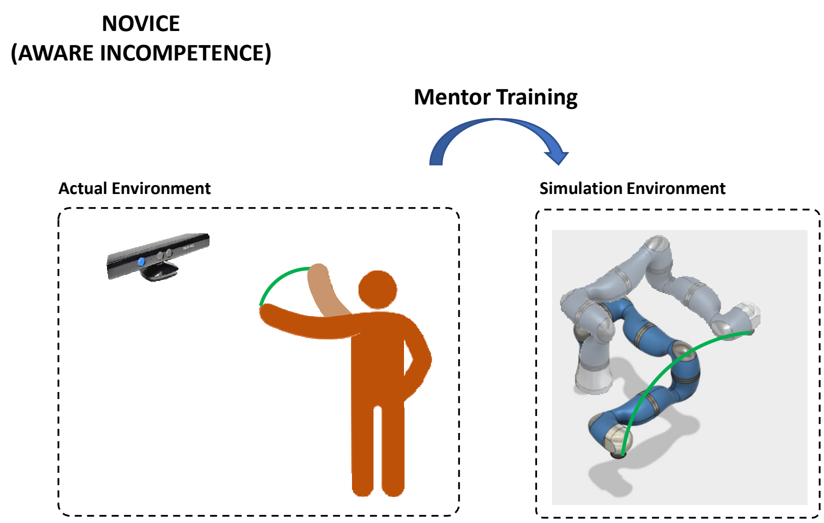


Figure 3. Experts demonstrate via a motion capture sensor to the robot how to travel on a trajectory to perform a specific task.

Figure 4 for illustrates an example of advanced novice stage, where we are still at aware incompetence but more practical scenarios can be investigated. Setting out 3D simulation and Digital Twin is used to provide a realistic simulation environment. Having defined the Domain and Goal for an Application specification as mentioned in the two prior stages above, and having developed a 3D Model/Simulation of the process, the concept of a Digital Twin is available. The Digital Twin is whereby design work can be conducted within the Simulation environment, and for this to map to the deliverable design in the Physical environment (i.e., the Robot physically executing the process in a test/development or production scenario). Changes in the Production scenario would be captured and changes made the Simulation environment and vice versa. The advantage of this is twofold: a) Simulation environments are based on physical models, and may be imperfect in comparison to the actual physical environment, and the capture of anomalies and divergence will help the simulation to improve; b) Once a test/development environment is deployed, changes will likely be ongoing as version upgrades to the environment and/or objects occur, causing maintenance of the process and Application specification.

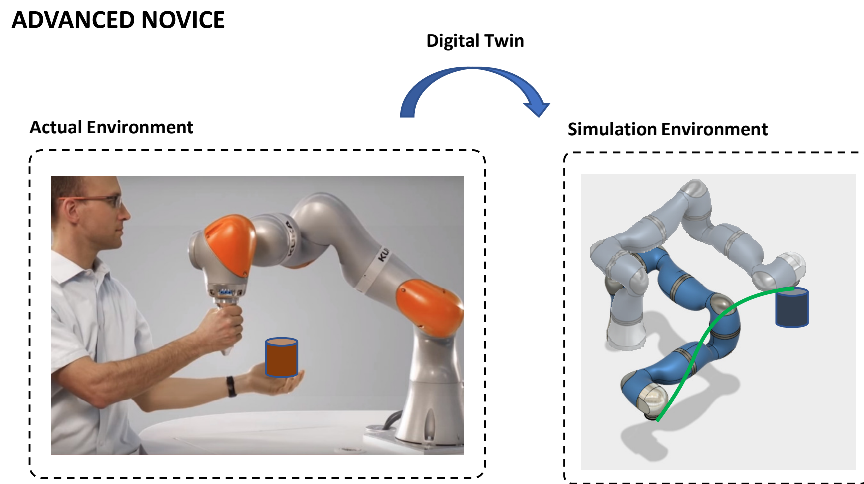


Figure 4. Digital twining as a tool to online monitoring of peripheral changes is employed to have a realistic simulation environment.

See Figure 5 for illustration example of beginning proficiency stage, where we are at an aware competence situation. Learning of possible schemas and stratagems with Twin Space (Design and Tests): In this case multiple scenarios can be tested to optimize the performance of the system. E.g., performance in terms of speed, wear and tear, power usage and precision may be set up as metrics for the characterization of the simulation and a multi-attribute utility analysis (a data science weighted selection matrix). Optimum solutions can be searched for, once the three prior stages are achieved.

See Figure 6 for illustration example of proficient stage, where we are still at an aware competence situation. However, we can start learning more sophisticated automation scenarios. As the knowledge base grows, the AI Planning and Optimization of Schemas/Stratagems (Reconfiguration and Test) can contribute more and more. Once many instances of optimization in the prior stage are undertaken, and captured in a structured data set, this data set can be subject to AI Machine Learning/Deep Learning to recognize the optimum schemas/stratagems. Simple articulation of the schemas/stratagems can be provided (e.g., schema X1 was selected).

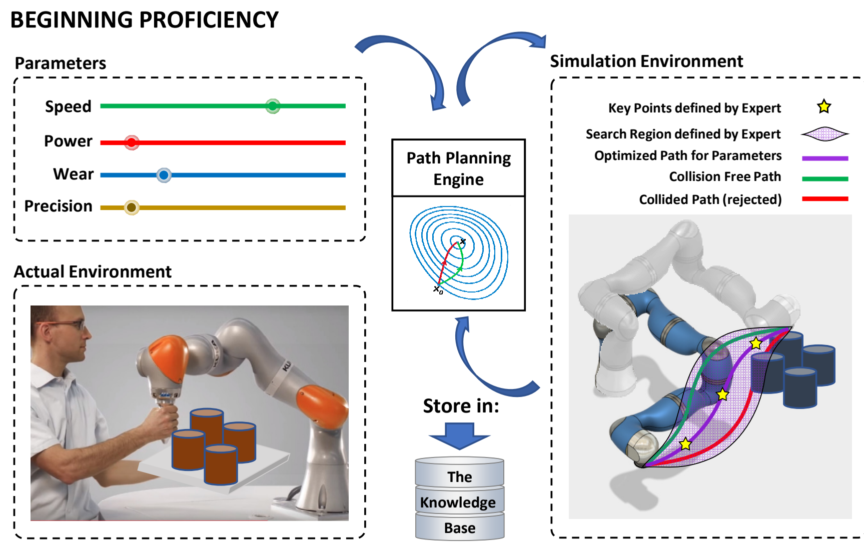


Figure 5. Multiple scenarios for different applications and tasks are collected and optimized through the digital twin equipped simulation environment and the results are stored as the knowledge base.

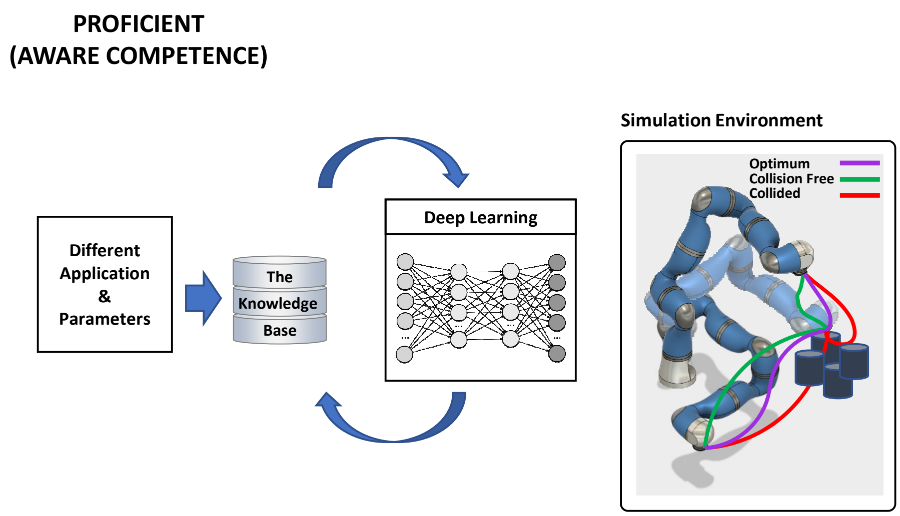


Figure 6. For different applications and tasks, the acquired knowledge base can be transferred into an actual AI framework using Deep Learning.

See Figure 7 for illustration example of expert stage, where we enter an unaware competence situation. AI Rationalization of Learned Schemas/Stratagems (Compliance and Explanation) is the eventual stage of the proposed work. It is anticipated that in many cases, there is in practice a need for automated system to be able to rationalize why it has selected a schema. E.g., to ensure there is compliance to a regulated requirement for process to conform to guidelines (not all processes, even apparently efficient ones may comply.) Deep Learning systems at the time of this application are recognized as having a weakness in this area [15]. Innovative "rule-extraction" systems that interrogate the Deep Learning systems and produce best fit rules that the system is performing against are a means for such compliance checking. The authors have filed a provisional patent application in this area [3].

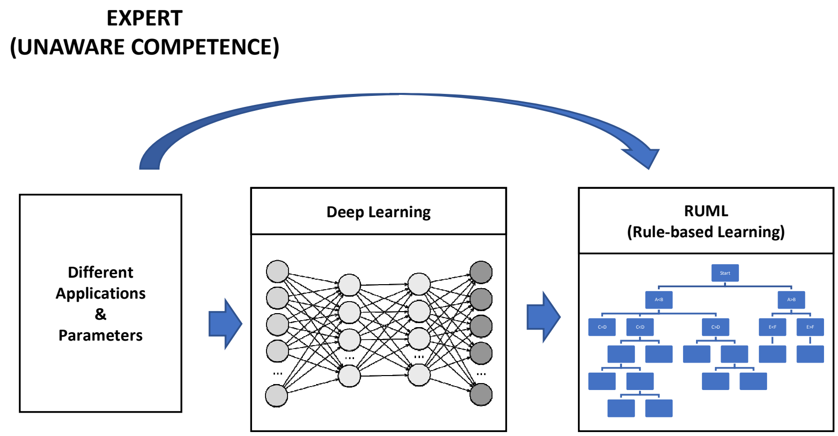


Figure 7. Gradually the rationalization of the relationship between the solution provided for different applications and tasks is obtained using a Really Useful Machine Learning.

## 3. CONCLUSION

An innovative computer system framework is presented that supports robot automation programming by a gesture controlled “show and tell” process, whereby human experts describe their goals of a process to be learned, and demonstrate via positional sensors the actions necessary to achieve those goals. These inputs are collected and optimized by the robot mentoring system, interpreted back to the human expert for confirmation feedback and/or subsequent fine tuning. This framework, is a pedagogical model, modelled on a professional human process needed to mentor others. We have applied this concept in an innovative way to mentor robots with gesture control and machine learning.

A six-stage training process from beginner to expert is provided by example, where the level of the expertise will transform from an unaware incompetence to unaware competence, then to aware competence, and eventually end up at an unaware competence where the rationalization of the trained skills is obtained. The proposed framework provides a holistic solution to automate the automation step-by-step using AI tools. The application of such a training framework can not only facilitate the manufacturing process but can also significantly accelerate the order-to-delivery process in industrial automation.

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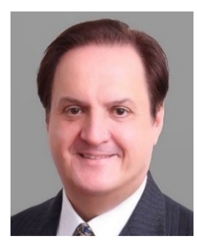

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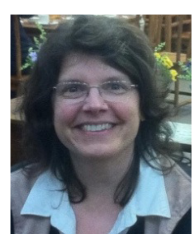

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