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Technical paper

A human-centric framework for robotic task learning and optimization

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ABSTRACT

One of the main objectives of the fifth industrial revolution is the design and implementation of human-centric production environments. The human is, indeed, placed in the center of the production environment, having a supervision/leading role instead of carrying out heavy/repetitive tasks. To enhance such an industrial paradigm change, industrial operators have to be provided with the tools they need to naturally and easily transfer their knowledge to robotic systems. Such expertise, in fact, is difficult to be coded, especially for non-expert programmers. In addition, due to the reduced specialized manpower, the capability to transfer such knowledge into robotic systems is becoming increasingly critical and demanding. In response to this need, this contribution aims to propose and validate a human-centric approach to transfer the human's knowledge of a task into the robot controller making use of qualitative feedback only (to this end, preference-based optimization is employed). In addition, the modeled human's knowledge is exploited by an optimization algorithm (*i.e.*, nonlinear programming) to maximize the task performance while managing the task constraints. The proposed approach has been implemented and validated for a robotic sealant material deposition task. On the basis of the qualitative feedback provided by the operator, the knowledge related to the deposition task has been transferred to the robotic system and optimized to deal with the hardware and task constraints. The achieved results show the generalization of the approach, making it possible to optimize the deposition task output.

1. Introduction

1.1. Context

Robotics is increasingly devoted to assisting humans in many different fields (such as rehabilitation, rescue, medical applications, etc.) [1–3]. A robotic system, therefore, has to enable and facilitate the task that the human has to execute, exploiting intelligent tools to capture the human's needs, requirements, instructions, feedback, and satisfaction [4]. One of the most important application areas is represented by industrial workplaces [5]. Industry 4.0 [6] is evolving to Industry 5.0 [7] by improving the working conditions of the industrial operators alongside making use of human knowledge, adaptability, and intelligence. One of the main objectives of this new industrial revolution is to move the attention from connected cyber–physical systems to operators, designing human-centric production environments exploiting human's knowledge to improve the industrial processes [8]. The human is placed in the center of the production environment, playing a leading role instead of carrying out manual (heavy/repetitive) tasks. In fact, the human should be involved in high-added-value operations (*i.e.*, all the operations in which the expertise of the human can be exploited to improve the production process), instead of performing easily automatable tasks [9]. Thus, to fully exploit the expertise of the operators, tools to naturally and easily transfer such knowledge to robotic systems are required.

The main contribution of this paper is, therefore, to propose and validate a human-centric approach to transfer the human's knowledge of a task into the robotic system, making use of qualitative feedback only. In such a way, non-expert programmers will be allowed to transfer their knowledge to robotic systems for the tuning of a target task.

In the following, the state of the art in the considered research area (*i.e.*, transferring the human's knowledge to the robotic system) is investigated, with a particular focus on preference-based optimization algorithms and their application to the robotic field.

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1.2. Related work

Robotics provides a set of tools to improve the working conditions of the operator [10], to physically assist him/her with collaborative robots [11] or exoskeletons [12], to implement AI-based solutions to train/guide the operator through a task [13], to ensure safety in the workplace [14], etc., with the main aim to design a human-centric workplace, where human intelligence can be exploited to enhance production, as aimed at by the Industry5.0 paradigm. However, current state-of-the-art approaches are still insufficiently capable of capturing the operator's task knowledge and transferring it to the robotic system. While the research community is working in the direction of programming by demonstration [15], knowledge extraction from quantitative data [16], graphical robot programming [17], or quantitative optimization approaches [18], these approaches still show many limitations in embedding the full human knowledge of a task (*i.e.*, the expertise of the human w.r.t. the behavior of the process, useful to perform tuning and/or adaptation of the process parameters to maximize the process output quality) into the robotic system. The knowledge transfer process is still complex (in terms of approaches, procedures, and required operator skills — such as programming), creating a barrier to its application in real working environments. In addition, generalization capabilities (*i.e.*, recalling the ability of the human to adapt his/her behavior to – partially – new situations) are not commonly well-addressed in order to transfer the knowledge of a learned task to a (partially) new one, limiting the intelligence of the robotic system.

Preference-based optimization [19,20] has been investigated in order to provide a solution to the above-mentioned issues. This approach makes use of qualitative human feedback for the optimization of a process, providing a powerful tool for such applications in which it is difficult to define and/or evaluate a quantitative performance index to design/compute an objective function. It is, in fact, usually simpler to express a preference such as "this is better than that" between two experiments. In this way, the preferences provided by the human allow for modeling its knowledge of a task/process. Indeed, researchers have put their attention on optimization methods to minimize black-box functions using preferences, such as employing Particle Swarm Optimization (PSO, [21,22]). Such an optimization drives the evolution of particles only based on the outcome of comparisons between the function values. Preference-based optimization has been also used in combination with Reinforcement Learning (RL) [23]. "Active preference learning" has been also investigated, in which the user iteratively expresses a preference. To this end, [24] presents a review of different active learning algorithms, such as the one developed in [25]. An important concept of PBO is represented by RBF functions, that have been studied in [26,27]. Despite preferences can be a powerful approach to optimize a robotic task [28], the preference-based optimization (PBO) technique has been employed only in a few robotic use cases. User's preferences have been combined with demonstrations to reduce the required number of queries [29], where a robotic manipulator is trained to reach a goal configuration while avoiding an obstacle. Calibration of model predictive control parameters based on user's preferences is discussed in [30]. In [31], a Bayesian deep learning method is proposed to optimize the parameters for a navigation task using humans' preference evaluations. In [32], PBO has been used to optimize a robotic sealant material deposition task. While the PBO has been successfully employed in the above-mentioned applications, its usage is still limited to highly specific and restricted situations. Based on its potential, the PBO can be employed to model the knowledge of the operator of a complex process, to be exploited for a generic task optimization, providing the robotic system with human-like flexibility/adaptability skills. The comparison of the proposed approach w.r.t. the state-of-the-art approaches exploiting active preference learning is shown in Table 1 for the considered features added by the proposed human-centric optimization framework.

1.3. Paper contribution

The main aim of this paper is to exploit the PBO in order to embed the human's knowledge of a task (*i.e.*, the expertise of the operator in manual task tuning/execution to maximize the process output quality) into a robotic system to optimize the execution of an industrial application. In particular, the expertise of the human operator is transferred to the robot by making use of qualitative feedback only. Such intelligence is then employed by an optimization algorithm (*i.e.*, nonlinear programming — NLP) to deal with task/hardware constraints, maximizing the task performance. In such a way, a human-centric task optimization approach can be implemented. The proposed approach has been applied to a robotic sealant material deposition task for its validation. In this specific application, the process output quality has to be maximized w.r.t. the following criteria: homogeneity of the deposition, absence of vibrations/instabilities, and target thickness of the deposited material achieved. While in [32] an advanced complex path-based velocity planner (only considering 4 types of geometrical features: straight lines, large curves, small curves, and very small curves) was used to manage the deposition task, a simple PID controller has been employed in this paper to operate the robot. Instead, the optimal reference deposition velocity has been tuned making use of the PBO, and varying the radius of the deposition path. In such a way, a model mapping the preference of the operator (*i.e.*, modeling the operator's knowledge of the deposition task) w.r.t. the deposition velocity and the path radius has been constructed. In addition, a model mapping the acceptability of the quality of the output of the deposition task w.r.t the deposition velocity and the path radius has been also constructed. These models have been employed in the NLP algorithm, together with the hardware constraints (*i.e.*, maximum acceleration limit), to optimize the reference velocity to execute the robotic deposition task. A Franka EMIKA panda robot has been used as a validation platform. The robot has been equipped with a MAKITA sealing gun operated by making use of a servomotor controlled with ARDUINO. The proposed approach has been able to optimize the considered deposition task output making use of the operator's knowledge, dealing with changing task conditions (*i.e.*, with different general-features paths), and showing generalization capabilities.

The main differences w.r.t. [32] can be summarized as:

- the complex velocity planner based on four geometrical features only proposed in [32] have been replaced with a general human-centric modeling providing for each radius of the deposition path the optimal deposition velocity and the acceptable deposition velocities range. In such a way, generalization capabilities are implemented, while reducing the complexity of the optimization procedure;
- a second optimization step has been introduced in order to globally optimize the deposition task, satisfying the hardware constraints (such as the acceleration constraint) and the ones provided by the operator (*i.e.*, on the acceptable deposition quality). W.r.t. [32], in which the computation of the deposition velocity is made only considering the forward portion of the path, in the proposed approach the optimization is made globally, taking into consideration the whole path.

The main novelties of this paper, indeed, are:

- to propose a human-centric knowledge transfer approach to provide a robotic system with the expertise of the operator (*i.e.*, modeling such a human's knowledge);
- to exploit such modeled knowledge to optimize a process, providing generalization capabilities (*i.e.*, to deal with different tasks conditions);
- to test and evaluate the performance of the proposed human-centric knowledge transfer approach in a real complex robotic task (*i.e.*, taking as a reference application a robotic sealant material deposition task).

Table 1
Proposed approach comparison with the other state of the art solutions analyzed in Section 1.2.

Reference	Human's knowledge transferred to robot	Global task optimization with task constraints	Task generalizability	Global task acceptability
[25]	✗	✗	✗	✗
[26]	✗	✗	✗	✗
[27]	✗	✗	✗	✓
[28]	✓	✗	✗	✗
[29]	✓	✗	✗	✗
[30]	✗	✓	✗	✗
[31]	✗	✗	✗	✗
[32]	✓	✗	✗	✓
Proposed approach	✓	✓	✓	✓

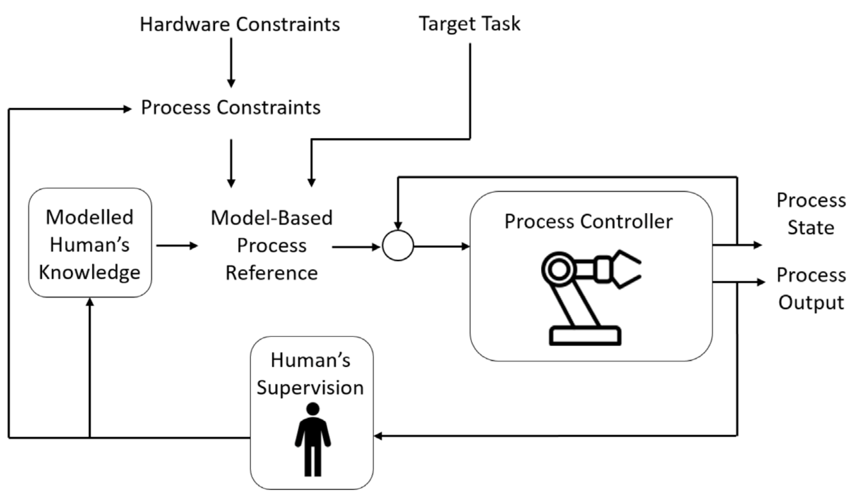

Fig. 1. Human's knowledge modeling employed in the process control: the modeled human's knowledge (obtained by the provided human's feedback) and the process constraints (*i.e.*, both provided by the human and related to the process itself) are used to generate the reference for the process controller for the optimization of the target task to be executed.

1.4. Paper layout

The rest of the paper is structured as follows: Section 2 details the proposed methodology, Section 3 describes the considered use case (*i.e.*, the robotic sealant material deposition task), Section 4 discusses the achieved results, and Section 5 states the conclusions of the paper.

2. Methodology

The main objective of this paper is to define a human-centric methodology allowing to embed into a robotic system the knowledge of an expert operator to maximize the target task quality. Fig. 1 shows the proposed approach, which is composed of five main components: *Human's Supervision*, *Modeled Human's Knowledge*, *Process Constraints*, *Model-Based Process Reference*, and *Process Control*. The first four components are defining the human-centric knowledge transfer approach proposed in this paper allowing to compute the process reference behavior to be performed, while the last one is related to the employed specific process control algorithm (*i.e.*, the robot controller) that exploits the mentioned computed process reference. More in detail, the *Human's Supervision* block is related to the qualitative feedback provided by the human on the process output quality, the *Modeled Human's Knowledge* block allows to model the expert human's task knowledge, the *Process Constraints* block allows to define the process and hardware constraints, and the *Model-Based Process Reference* block allows to optimize the process reference based on the output of the previous blocks and on the target task to be executed *Target Task*. In particular, considering the *Process Constraints* block, it is possible to embed in such modeling some useful knowledge of the human operator, *e.g.*, related to the process quality. In this paper, the process acceptability information are embedded in this block in order to provide additional constraints on the quality of the target process, guaranteeing that the process output quality satisfies a target standard.

In the following, each block composing the proposed approach is individually described in order to provide all the details related to the diagram in Fig. 1.

2.1. Preference-based optimization

The preference-based optimization is employed in the proposed approach in Fig. 1 in the *Modeled Human's Knowledge* block. In fact, by making use of such a technique it is possible to embed the knowledge and skills of the expert operator into the robotic system by only means of qualitative human's feedback (highlighted by the *Human's Supervision* block). Such modeling allows computing the optimal process reference for the target task.

The preference-based optimization algorithm employed in this paper is based on the methodology developed in [27] by some of the authors, where the GLISp algorithm is introduced.

2.1.1. Building a surrogate function from preferences

The first step of the GLISp algorithm is to build a surrogate function describing the observed preferences.

Formally, given two possible sets of parameters θ_1 and θ_2, the *preference function* $\pi : \mathbb{R}^{n_\theta} \times \mathbb{R}^{n_\theta} \to \{-1, 0, 1\}$ is defined as:

$$\pi(\theta_1, \theta_2) = \begin{cases} -1 & \text{if } \theta_1 \text{ “better” than } \theta_2 \\ 0 & \text{if } \theta_1 \text{ “as good as” } \theta_2 \\ 1 & \text{if } \theta_2 \text{ “better” than } \theta_1. \end{cases} \tag{1}$$

Assuming that $N \geq 2$ samples $\{\theta_1 \; \dots \; \theta_N\}$ of the decision vector are generated, with $\theta_i, \theta_j \in \mathbb{R}^{n_\theta}$ such that $\theta_i \neq \theta_j$, $\forall i \neq j$, with $i, j = 1, \dots, N$. For each of these parameters, an experiment is performed and the user provides a *preference vector* $\mathbf{B} = [b_1 \ \dots \ b_M]^T \in \{-1, 0, 1\}^M$ with:

$$b_h = \pi(\theta_{i(h)}, \theta_{j(h)}), \tag{2}$$

where M is the number of expressed preferences, $h \in \{1, \dots, M\}$, $i(h), j(h) \in \{1, \dots, N\}$, and $i(h) \neq j(h)$. It has to be noted that the element b_h of the vector the $\mathbf{B}$ represents the preference expressed by the user between the experimental performance achieved with the parameters $\theta_{i(h)}$ and $\theta_{j(h)}$.

The observed preferences are then used to learn a surrogate function $\hat{J} : \mathbb{R}^{n_\theta} \to \mathbb{R}$ of an (unknown) underlying performance index J. The surrogate $\hat{J}$ is parametrized as the following linear combination of Radial Basis Functions (RBFs):

$$\hat{J}(\theta) = \sum_{k=1}^{N} \beta_k \phi(\gamma d(\theta, \theta_i)), \tag{3}$$

where $d : \mathbb{R}^{n_\theta} \times \mathbb{R}^{n_\theta} \to \mathbb{R}$ is the squared Euclidean distance:

$$d(\theta, \theta_i) = \|\theta - \theta_i\|_2^2, \tag{4}$$

$\gamma > 0$ is a scalar parameter, $\phi : \mathbb{R} \to \mathbb{R}$ is an RBF, and $\beta = [\beta_1 \ \dots \ \beta_N]^T$ are the unknown coefficients to be computed based on the available user's preferences. Examples of RBFs are $\phi(\gamma d) = \frac{1}{1+(\gamma d)^2}$ (*inverse quadratic*) and $\phi(\gamma d) = e^{-(\gamma d)^2}$ (*Gaussian*) (see [27] for more details).

According to the preference relation (1), the surrogate $\hat{J}$ has to satisfy the following constraints:

$$\begin{array}{ll} \hat{J}(\theta_{i(h)}) \le \hat{J}(\theta_{j(h)}) - \sigma + \varepsilon_h & \text{if } \pi(\theta_{i(h)}, \theta_{j(h)}) = -1 \\ \hat{J}(\theta_{i(h)}) \ge \hat{J}(\theta_{j(h)}) + \sigma - \varepsilon_h & \text{if } \pi(\theta_{i(h)}, \theta_{j(h)}) = 1 \\ |\hat{J}(\theta_{i(h)}) - \hat{J}(\theta_{j(h)})| \le \sigma + \varepsilon_h & \text{if } \pi(\theta_{i(h)}, \theta_{j(h)}) = 0 \end{array} \tag{5}$$

for all $h = 1, \dots, M$, where $\sigma > 0$ is a given tolerance and ε_h is a positive slack variable that is used to relax the preference constraints. Constraints infeasibility might be due to an inappropriate selection of the RBF (namely, poor flexibility in the parametric description of the surrogate $\hat{J}$) and/or inconsistent assessments done by the user.

Based on the above preference constraints, the coefficient vector β describing the surrogate $\hat{J}$ is obtained by solving the Quadratic Programming (QP) problem:

$$\begin{array}{ll} \min_{\beta,\varepsilon} & \sum_{h=1}^{M} \varepsilon_h + \frac{\lambda}{2} \sum_{k=1}^{N} \beta_k^2 \\ \text{s.t.} & \sum_{k=1}^{N} (\phi(\gamma d(\theta_{i(h)}, \theta_k)) - \phi(\gamma d(\theta_{j(h)}, \theta_k)))\beta_k \\ & \quad \le -\sigma + \varepsilon_h, \qquad \forall h: \ b_h = -1 \\ & \sum_{k=1}^{N} (\phi(\gamma d(\theta_{i(h)}, \theta_k)) - \phi(\gamma d(\theta_{j(h)}, \theta_k)))\beta_k \\ & \quad \ge \sigma - \varepsilon_h, \qquad \forall h: \ b_h = 1 \\ & \left| \sum_{k=1}^{N} (\phi(\gamma d(\theta_{i(h)}, \theta_k)) - \phi(\gamma d(\theta_{j(h)}, \theta_k)))\beta_k \right| \\ & \quad \le \sigma + \varepsilon_h, \qquad \forall h: \ b_h = 0 \\ & h = 1, \dots, M. \end{array} \tag{6}$$

The scalar $\lambda > 0$ in the cost function (6) is a regularization parameter that guarantees uniqueness in the solution of the QP problem.

2.1.2. Acquisition function

Once a surrogate $\hat{J}$ is estimated, this function can be minimized in order to find the optimal parameter vector θ.

More in detail, the following steps can be followed:

(i) generate a new sample by pure minimization of the estimated surrogate function $\hat{J}$, *i.e.*,

$$\theta_{N+1} = \arg\min \hat{J}(\theta) \ \text{ s.t. } \ \theta \in \Theta;$$

(ii) ask the user to express a preference $\pi(\theta_{N+1}, \theta_N^\star)$, where $\theta_N^\star \in \mathbb{R}^{n_\theta}$ is the vector of parameters with the best experimental output (judged by the user) found so far;

(iii) update the estimate of $\hat{J}$ through (6);

(iv) iterate over N.

Such a procedure, which only *exploits* the current available observations in finding the optimal parameter vector θ, may easily miss a more performing set of parameters. Indeed, a term promoting the *exploration* of the parameter space should be considered.

In the GLISp algorithm, an acquisition function is employed to balance exploitation *vs.* exploration when generating the new sample θ_{N+1}. The exploration function is defined by using the inverse distance weighting (IDW) function $z : \mathbb{R}^{n_\theta} \to \mathbb{R}$ defined as:

$$z(\theta) = \begin{cases} 0 & \text{if } \theta \in \{\theta_1, \dots, \theta_N\} \\ \tan^{-1}\left(\frac{1}{\sum_{i=1}^{N} w_i(\theta)}\right) & \text{otherwise,} \end{cases} \tag{7}$$

where $w_i(\theta) = \frac{1}{d^2(\theta, \theta_i)}$. Clearly, $z(\theta) = 0$ for all parameters already tested, and $z(\theta) > 0$ in $\mathbb{R}^{n_\theta} \setminus \{\theta_1, \dots, \theta_N\}$. The arc tangent function in (7) avoids that $z(\theta)$ gets excessively large far away from all sampled points.

Then, given an exploration parameter $\delta \ge 0$, the *acquisition function* $a : \mathbb{R}^{n_\theta} \to \mathbb{R}$ is constructed as:

$$a(\theta) = \frac{\hat{J}(\theta)}{\Delta\hat{J}} - \delta z(\theta), \tag{8}$$

where

$$\Delta\hat{J} = \max_i\{\hat{J}(\theta_i)\} - \min_i\{\hat{J}(\theta_i)\}$$

is the range of the surrogate function on the samples in $\{\theta_1, \dots, \theta_N\}$ and used in (8) as a normalization factor to simplify the choice of the exploration parameter δ.

Given a set $\{\theta_1, \dots, \theta_N\}$ of samples and a vector $\mathbf{B}$ of preferences defined in (2), the next parameter set θ_{N+1} to be tested is computed as the solution of the (non-convex) optimization problem:

$$\theta_{N+1} = \arg\min_{\theta \in \Theta} a(\theta). \tag{9}$$

2.1.3. Pseudocode

The pseudocode of the employed preference-based optimization is detailed in Algorithm 1. The schematic representation of the *Modeled Human's Knowledge* block is shown in Fig. 2.

Algorithm 1 PBO's pseudocode

```
θ ← [θ_1, θ_2, .., θ_N]
b_in ← [[θ_1, θ_2], [θ_2, θ_4], ...[θ_h, θ_k]]
b_eq ← [[θ_2, θ_3], ..., [θ_z, θ_y]]
my_pbo ← PBO(θ, b_in, b_eq)
my_pbo.update()
for i →iterations do
    θ_{N+1} ←my_pbo.run_optimization()
    if θ_{N+1} as good as than θ_best then
        eval ← 0
    else
        if θ_{N+1} better than θ_best then
            eval ← −1
        else
            eval ← 1
        end if
    end if
    my_pbo.add_evaluation(θ_{N+1}, eval)
    my_pbo.update()
end for
```

The pseudo-code represented in Algorithm 1 summarizes the preference-based optimization approach, and the involved quantities are described below:

- θ: contains the points already tested;

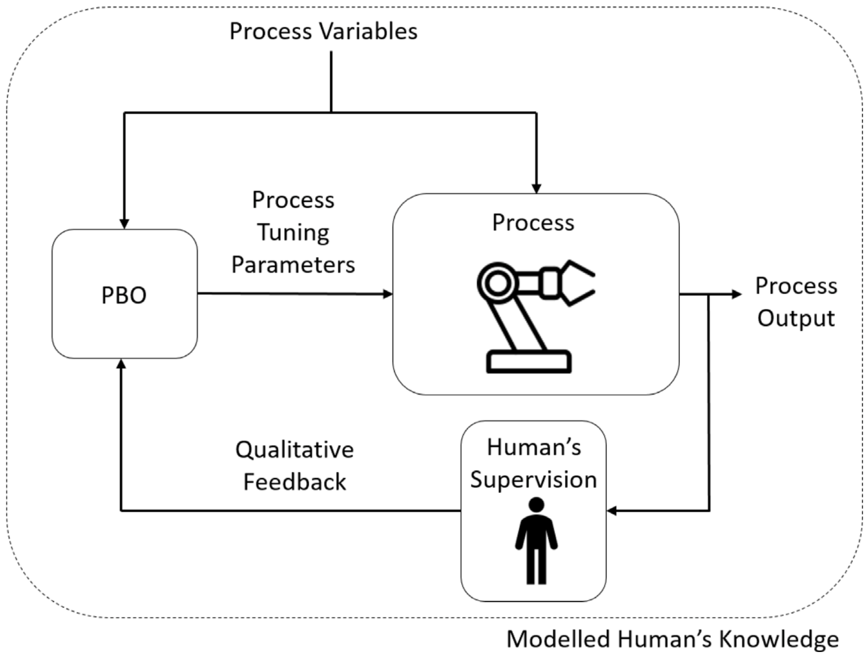

Fig. 2. The schematic representation of the *Modeled Human's Knowledge* block is shown. The human's knowledge is gathered making use of the PBO, iteratively executing experimental tests for the optimization of the process tuning parameters for the considered process variables (*i.e.*, operative conditions), and exploiting the qualitative feedback provided by the user on the process output quality.

- $\mathbf{b}_{in}$: pairwise comparisons $[\theta_h, \theta_k]$, where θ_h is "better" than θ_k (as in (1), $\pi(\theta_h, \theta_k) = -1$);
- $\mathbf{b}_{eq}$ pairwise comparisons $[\theta_z, \theta_y]$, where θ_z is "as good as" θ_y (as in (1), $\pi(\theta_z, \theta_y) = 0$).

2.2. Task acceptability

In the construction of the acquisition function $a(\theta)$ discussed above, the user's satisfaction criteria (*i.e.*, the task acceptability) for the target task was not considered. However, the satisfaction of the user on the executed task can be useful information to be exploited in the choice of the next parameter θ_{N+1}, thus penalizing configurations of the velocity planner which are expected to provide unsatisfactory performance.

In order to include this information, an independent binary-classification Gaussian Process is trained based on the user's satisfaction of previous experiments. Such a Gaussian Process maps the parameter vector θ into the probability of achieving satisfactory quality performance. If this probability is below a given threshold (50% in the considered application) a penalty function is then added to the acquisition function $a(\theta)$.

The acceptability modeling is then employed in the proposed approach in Fig. 1 in the *Process Constraints* block. Together with the hardware constraints, such modeling provides additional information to the *Model-based Process Reference* block (*i.e.*, the NLP in this paper) to perform the optimization of the task reference satisfying the provided constraints. The acceptability modeling, indeed, allows guaranteeing an acceptable process output in the case that the optimal one cannot be guaranteed due to the other process/hardware constraints.

2.3. Nonlinear programming

The *Model-based Process Reference* block in Fig. 1 makes it possible to compute a globally optimized process reference satisfying the constraints provided by the *Process Constraints* block (which are defined based on the human's knowledge and hardware constraints) for the execution of the *target task*. NLP is employed in this paper to implement such a component in the proposed methodology. As in [33], a smooth constrained optimization problem can be defined to minimize an objective function $f(\mathbf{x})$ under nonlinear inequality constraints

$$\begin{aligned} \min_{\mathbf{x}} \quad & \sum_{\mathbf{x}} f(\mathbf{x}) \\ \text{s.t.} \quad & \mathbf{g}(\mathbf{x}) \leq 0 \end{aligned} \tag{10}$$

where $\mathbf{x}$ is an n-dimensional vector defining the optimization variables. $\mathbf{g}(\mathbf{x})$ defines m inequality constraints $g_i(\mathbf{x})$. The defined optimization problem is indeed embedded into the *Model-based Process Reference* block for the optimization of the task, making use of the task constraints $\mathbf{g}(\mathbf{x})$ (both related to human's task knowledge and the task itself).

3. Use case: robotic sealant material deposition task

3.1. Task description

In order to evaluate the performance of the proposed human-centric process tuning approach, a robotic sealant material deposition task is considered as a use case. The tuning of such a task, in fact, can benefit from the human's task knowledge/judgment to maximize the deposition performance, instead to make use of external measurement systems (such as laser scanners, being costly and requiring additional integration and software for data processing) and quantitative performance indexes (difficult to be defined to catch the different process behaviors) for the definition of an objective function. Indeed, human's qualitative feedback can be intuitively provided to the *Modeled Human's Knowledge* block (*i.e.*, to the employed PBO), allowing to transfer the human's task knowledge to the robotic system.

The main objective of the task is, therefore, to perform a high-quality material deposition along any generic path. The performance of the robotic deposition are evaluated by the operator in terms of homogeneity, absence of vibrations, and quantity of deposited material.

The deposition task velocity (*i.e.*, the velocity of the robot end-effector) has been considered as the optimization variable of the PBO to maximize the deposition quality. Indeed, the deposition task velocity affects the deposition quality: it has to be tuned to guarantee the correct quantity of deposited material. In fact, if the robot is too slow, too much material will be deposited, while if the robot is too fast, too

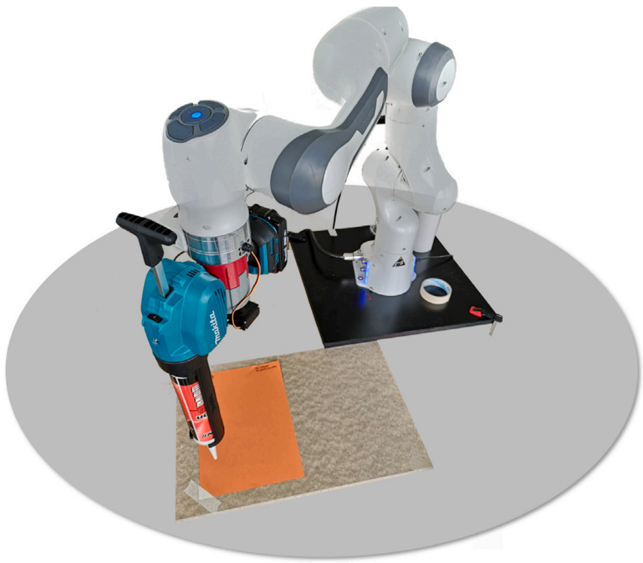

Fig. 3. Experimental setup for the evaluation of the proposed human-centric process tuning approach. A robotic sealant material deposition task has been performed to validate the proposed methodology. A Franka EMIKA panda robot is equipped with a MAKITA sealing gun, operated by a servomotor (controlled with Arduino).

little material will be deposited. The deposition task velocity has to be optimized for different path radii in order to model the deposition process behavior. Making use of the general model (*i.e.*, mapping the optimal velocity w.r.t. the path radius) it will be possible to optimize the deposition task velocity along any general deposition path.

Considering the target robotic deposition task, the proposed human-centric process tuning approach allows to compute the reference deposition velocity to maximize the quality of the deposition task. Such a reference velocity is given as input to the robot motion controller for the execution of the deposition task. The robot controller, indeed, has to be capable to follow such a reference velocity to guarantee the correct task execution.

Remark 1. It has to be underlined that the material flow cannot be regulated with the employed deposition gun (*i.e.*, the material flow is fixed). In addition, it has to be considered that even if the material flow can be tuned, its effect will be the same as for the tuning of the deposition task velocity. Therefore, the optimization problem can be simplified by only considering one optimization variable.

3.2. Materials

Fig. 3 shows the reference robotic sealant material deposition task. The experimental setup consists of a Franka EMIKA panda robot, equipped with a MAKITA sealing gun, operated by making use of a servomotor controlled with Arduino. The robot is controlled by exploiting its torque control (control frequency: 1000 Hz). A PID trajectory controller has been implemented and tuned on the basis of the work in [34]. Such a low-level controller makes use of the reference deposition velocity provided by the proposed human-centric process tuning approach to perform the task, guaranteeing the required motion-tracking performance. The software has been developed within the ROS framework.

3.3. Modeling the human's knowledge through the PBO

In order to model the human's knowledge to be embedded into the *Modeled Human's Knowledge* and *Process Constraints* blocks for the considered deposition task, a set of deposition radii r_i has been considered as it follows: $r_i \in [10, 100]$ mm, with a step equal to 6 mm. For each deposition radius, the PBO has been applied to optimize the deposition task velocity (*i.e.*, to achieve the best possible deposition quality in terms of homogeneity, absence of vibrations, and quantity of deposited material), modeling the human's knowledge (*i.e.*, into the *Modeled Human's Knowledge* block) to be exploited for the deposition task optimization (*i.e.*, into the *Model-Based Process Reference* block). For each experimental trial (suggested by the PBO, as described in Section 2.1), additional information related to the acceptability of the deposition task quality is provided. Such information is then embedded into the *Process Constraints* block (as detailed in Section 2.2) to provide the *Model-Based Process Reference* block with human's knowledge-based task constraints.

Remark 2. W.r.t. [32], the here proposed approach allows guaranteeing the generalization of the human's knowledge transfer to the robotic system. In fact, in this work, the general process behavior can be modeled and exploited for the optimization of the target task. Instead, in [32], only a restricted number of geometrical features have been considered, without taking into consideration their optimization (*i.e.*, might not be able to optimally describe the process behavior).

Remark 3. The employed PBO is shown to be efficient in terms of required experimental trials for the optimization of a process [27]. Indeed, it is extremely powerful to be employed in the proposed human-centric process tuning approach as it requires the tuning of the process in different conditions (*i.e.*, varying the path radius).

3.3.1. Human preference evaluation procedure

The following evaluation procedure has been implemented to collect the human preferences (*i.e.*, to judge the deposition output) for each tested path radius (see Section 3.3) to update the *Modeled Human's Knowledge* block (to be used by the PBO, see Section 2.1):

1. at each optimization iteration of the PBO, a deposition velocity (that is the optimization variable to be optimized, see Section 3.3) is proposed to be tested (*i.e.*, the deposition velocity is applied for the considered path radius to obtain the related deposition output required for the human judgment process);
2. the preference among the last deposition output (*i.e.*, obtained making use of the deposition velocity proposed by the last optimization iteration of the PBO) and the best one so far (*i.e.*, the global preference of the human until the last optimization iteration) is performed by the operator, *i.e.*, providing the preference among the two task outputs and indicating the preferred deposition velocity. The preference is given to the deposition output satisfying the most the operator, taking into consideration the criteria on the homogeneity of the deposition, absence of vibrations, and target thickness of the deposited material. The preference and the pair of evaluated deposition velocity values are given to the PBO algorithm [27];
3. the PBO computes the next deposition velocity (that is the target optimization variable for the considered use case) to be tested;
4. the procedure is repeated from 1.

Such a procedure allows the definition of the optimal velocity for each path radius, to be used by the NLP to optimize the deposition task execution for any general deposition path.

3.3.2. Acceptability evaluation procedure

The following evaluation procedure has been implemented to collect the acceptability judgments (*i.e.*, to evaluate if the deposition output quality related to the tested deposition velocities provided by the PBO is globally acceptable or not — *i.e.*, if the output quality satisfies the minimum quality requirements) for each tested path radius (see Section 3.3) to update the *Process Constraints* block (to be used by the NLP, see Section 2.3):

1. at each optimization iteration of the PBO, the deposition output quality is judged as *acceptable* or *not acceptable* by the operator. To be acceptable, it should satisfy the minimum quality requirements related to the following criteria: homogeneity of the deposition, absence of vibrations, and target thickness of the deposited material;
2. the acceptability index is given with a value equal to 1 if the deposition output is *acceptable*, and with a value equal to 0 if *not acceptable*;
3. the acceptability is modeled making use of binary-classification Gaussian Process (see Section 2.2) to be used into the proposed NLP (see Section 2.3);
4. the procedure is repeated from 1.

Such a procedure allows the definition of an acceptable deposition velocity range (*i.e.*, making use of a velocity in such a range, the deposition output quality results *acceptable*, and, therefore, the task can be considered correctly executed) for each path radius to be used by the NLP as a constraint for the global optimization phase.

3.4. Task optimization implementation

Employing the NLP as described in Section 2.3, it is possible to optimize the proposed deposition task by customizing the objective function in (10), taking also into consideration the task constraints. In particular, NLP aims to assign the optimum speed to each path radius, taking into account the following two hard constraints:

- acceleration has to be kept lower than the maximum allowed acceleration a_{max}: this constraint allows to avoid any hardware limit violation;
- deposition velocity within the acceptability range: this constraint allows to guarantee an acceptable deposition quality in the case that the optimal deposition velocity cannot be guaranteed.

In the following, the terms involved in the optimization problem are detailed.

3.4.1. Parameters

The parameters involved in the optimization problem are defined as it follows:

- **R**: radii vector containing for each point of the path the corresponding path radius r_i;
- **LB**: vector containing the lower bound velocities (defined by the acceptability range of the velocity as described in Section 3.3) related to each radius r_i in **R**;
- **UB**: vector containing the upper bound velocities (defined by the acceptability range of the velocity as described in Section 3.3) related to each radius r_i in **R**;
- **OPT**: vector containing the optimal velocity related to each radius r_i in **R**, computed making use of the PBO;
- **d**: vector containing the distance between the path points i and $i+1$ in its element d_i.

The target general path to be executed is given as an input to the NLP so that the radii vector **R** can be computed.

The variable to optimize is the deposition velocity v_i for each radius contained in **R**. The optimized velocity vector **v**, indeed, contains the deposition velocities to be executed along the target path.

3.4.2. Objective function

The objective function in (10) is defined to minimize the difference between the optimal velocity corresponding to the path radius r_i in **R** and the computed one (*i.e.*, v_i), respecting the task constraints:

$$\sum_{i=1}^{n-1} |v_i - OPT_i|, \tag{11}$$

where n is the number of path points.

3.4.3. Hard constraint

The optimized velocity vector **v** has to respect the two above-defined constraints, as it is generally defined in (10).

W.r.t. the constraint related to the acceleration limit a_{max}, this is a nonlinear constraint. Such a constraint can be written as it follows to highlight the nonlinearity:

$$\frac{|v_i - v_{i+1}| v_{i+1}}{d_{i,i+1}} \le a_{max}. \tag{12}$$

W.r.t the constraint on the acceptability of the deposition output (*i.e.*, defining the acceptable velocity range), this constraint can be written as it follows:

$$LB_i \le v_i \le UB_i. \tag{13}$$

3.4.4. Assembled NLP

The assembled NLP (*i.e.*, including the definitions in Sections 3.4.1, 3.4.2, and 3.4.3) results in the definition of the optimization parameters:

$$\begin{aligned}
\mathbf{R} &= [r_1, r_2, r_3, \dots, r_n]^T, \\
\mathbf{LB} &= [LB_1, LB_2, LB_3, \dots, LB_n]^T, \\
\mathbf{UB} &= [UB_1, UB_2, UB_3, \dots, UB_n]^T, \\
\mathbf{OPT} &= [OPT_1, OPT_2, OPT_3, \dots, OPT_n], \\
\mathbf{d} &= [d_1, d_2, d_3, \dots, d_{n-1}, 0],
\end{aligned} \tag{14}$$

and in the definition of the following objective function (with defined constraints):

$$\begin{aligned}
\min_{\mathbf{v}} \quad & \sum_{i=1}^{n-1} |v_i - OPT_i| \\
\text{s.t.} \quad & v_i \le UB_i \\
& v_i \ge LB_i \\
& \frac{|v_i - v_{i+1}| v_{i+1}}{d_i} \le a_{max} = 150 \text{ mm/s}
\end{aligned} \tag{15}$$

4. Experimental results

This Section provides the experimental results related to the human's knowledge modeling and to the evaluation of the proposed human-centric process tuning approach applied to the robotic sealant material deposition task.

A video showing the implementation of the proposed approach, together with the experimental testing, is available at the following link: https://youtu.be/UyrPkl_iUKQ. In the following, the results shown in the video are discussed.

4.1. Training results

The procedure described in Section 3.3 to model the human's knowledge has been employed to derive the optimal deposition task velocity and the acceptable deposition task velocity range among the path radius. Fig. 4 shows the PBO experimental trials output of a path radius (*i.e.*, $r_i = 64$ mm), ordered as suggested by the PBO. As it can be seen, the deposition output is affected by the deposition task velocity (*i.e.*, the robot end-effector velocity). Each deposition output has been judged (as detailed in Section 2.1 and in Section 2.2) in order to model the human's knowledge of the task (to obtain both the optimal velocity and the acceptable velocity range). The evolution of the human's preference among the PBO iterations (considering $r_i = 64$ mm) is shown on the left-side of Fig. 5, while the acceptability judgment for each PBO iteration is shown on the right-side of the same Figure.

By repeating such an optimization procedure for all the considered radii, the modeling for the optimal velocity and for the acceptable velocity range can be obtained. Fig. 6 shows the achieved modeling. The resulting modeling for the optimal velocity and for the acceptable

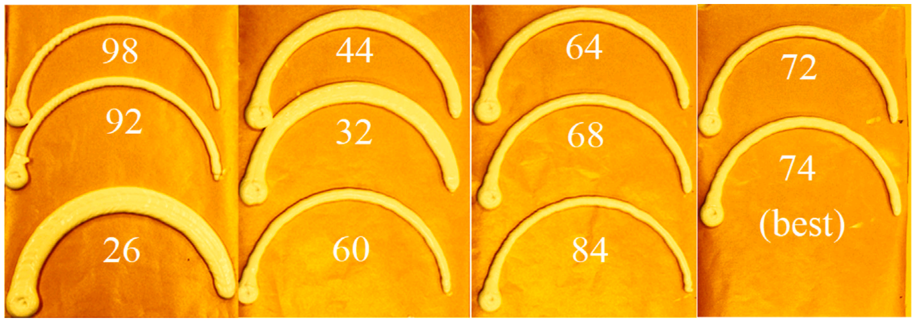

Fig. 4. PBO experimental trials output for the tuning of the path radius $r_i = 64$ mm. The following deposition task velocities (mm/s) have been suggested by the PBO (ordered based on the PBO suggestion): 98, 92, 26, 44, 32, 60, 64, 68, 84, 72, 74. The preferred deposition velocity among all the optimization iterations is 74.

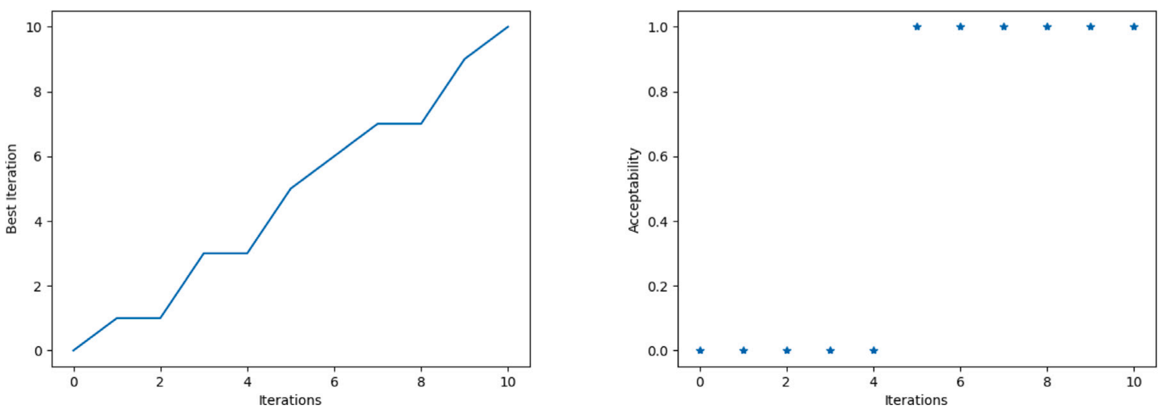

Fig. 5. On the left-side of the Figure, the evolution of the human's preference w.r.t. the PBO iterations is shown. On the right-side of the Figure, the acceptability judgment (*i.e.*, 0 for the *not acceptable* deposition and 1 for the *acceptable* deposition) is provided w.r.t. the PBO iterations. Both plots are related to the optimization of the path radius $r_i = 64$ mm, as in Fig. 4.

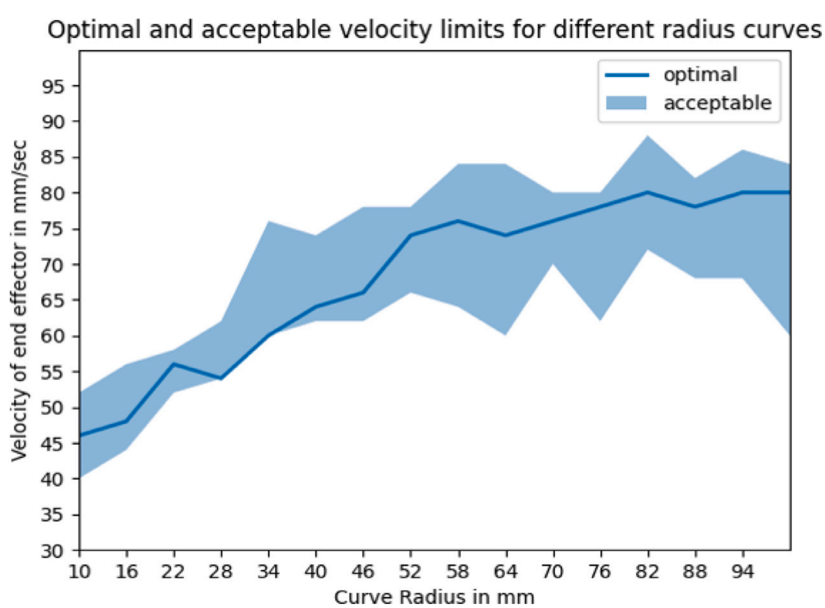

Fig. 6. Optimal deposition task velocity (blue line) and acceptable deposition task velocity range (light-blue velocity range) w.r.t. the path radius obtained by employing the PBO for the modeling of the human's task knowledge and the acceptability judgment.

velocity range (described in Section 2.1 and in Section 2.2, respectively) allows to embed the human's knowledge into the *Modeled Human's Knowledge* block, to be used for the task optimization purpose.

The proposed PBO requires between 10 and 12 optimization iterations for each radius to be optimized, taking between 5 to 6 minutes. To generate an accurate enough model, 16 radii have been independently optimized, for a total of 163 deposition experiments and between 80 and 95 minutes for the complete execution of the PBO over all the considered radii. Such an optimization procedure is indeed very fast and efficient to be performed in real applications.

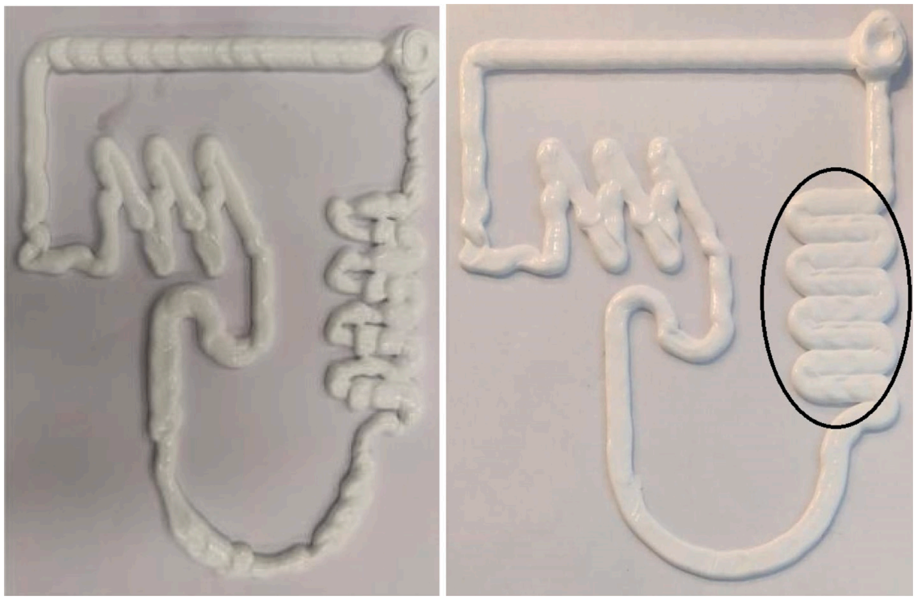

Fig. 7. Obtained deposition output without (left-side image) and with (right-side image) the usage of the *Model-Based Process Reference* block. As it can be seen, the deposition output quality is improved by employing the proposed model-based optimization block exploiting the modeled human's knowledge.

The obtained optimal velocity modeling has been embedded into the *Modeled Human's Knowledge* block, while the acceptable velocity range modeling has been embedded into the *Process Constraints* block, together with an additional process constraint on the acceleration, setting such a limit equal to 150 mm/s^2.

Remark 4. It has to be underlined that the maximum path radius r_i = 100 mm has been considered due to the fact that, as shown in Fig. 6, a saturation value for the optimal velocity is reached for higher radii. Indeed, for path radius $r_i \geq 100$ mm the same optimal velocity and acceptable velocity range are taken as for $r_i = 100$ mm (*e.g.*, for a straight line, the same values for the optimal velocity and acceptable velocity range are used as the ones of $r_i = 100$ mm).

Remark 5. The acceleration limit has been set on the basis of the employed hardware. Such a constraint (or additional ones) can be adapted (or even optimized making use of the PBO) on the basis of the considered process/hardware.

4.2. Validation results

In order to evaluate the effect of the *Model-Based Process Reference* block optimizing the deposition task exploiting both the optimal velocity modeling and the task constraints, Fig. 7 shows the deposition output without (left-side image) and with (right-side image) its usage. As it can be seen, the *Model-Based Process Reference* block plays an important role in order to exploit the modeled human's knowledge and the additional task constraints to guarantee the target task quality. The related velocity profiles along the curvilinear axis of the deposition path are shown in Fig. 8, in order to highlight the effect on the deposition task velocity related to the *Model-Based Process Reference* block. As it can be seen, the *Model-Based Process Reference* block allows modulating the deposition velocity to satisfy the task constraints (*i.e.*, related to the acceptable deposition velocity and to the acceleration limit). The thickness of the deposited material has been also measured in 45 positions along the path in order to quantify the homogeneity of the deposition. Table 2 shows the mean and the standard deviation of such measurements for both the depositions in Fig. 7. As it can be seen, employing the proposed human-centric approach for task optimization, a highly homogeneous deposition is achieved (standard deviation of the measured thickness equal to 0.862 mm). Instead, taking into consideration the not-optimized path, the deposition homogeneity becomes worse (standard deviation of the measured thickness equal to 1.63 mm, *i.e.*, the double w.r.t. the one obtained with the optimized path). Comparing the obtained deposition thickness mean value (10.477 mm) w.r.t. the one obtained by the PBO for the different radii (10.25 mm, computed taking into consideration all the optimal – *i.e.*, based on the user's preference – depositions for each radius), it can be highlighted that the proposed human-centric approach is capable to guarantee a target task quality as expected by the operator.

Table 2
Deposited thickness mean and standard deviation values as for the task output in Fig. 7 computed taking 45 measurements along the path.

	Mean [mm]	Standard deviation [mm]
Not-optimized path (left-side Fig. 7)	7.81	1.63
Optimized path (right-side Fig. 7)	10.477	0.862

Other two additional deposition paths have been tested as it is shown in Fig. 9, making use of the proposed human-centric process tuning approach. As it can be highlighted, the proposed approach allows embedding and exploit for optimization purposes of the task knowledge of the operator, allowing them to perform any general task achieving the target quality.

4.3. Comparison results

The performance of the proposed human-centric approach have been compared with the ones achieved by making use of the Programming by Demonstration (PbD) approach in [4], and with the ones achieved by making use of the velocity planner in [32]. Fig. 10 shows the deposition output obtained making use of the PbD approach in [32] (left-side of the Figure), the deposition output obtained making use of the velocity planner in [32] (center of the Figure), and the deposition output obtained with the proposed human-centric approach (right-side of the Figure). W.r.t. the PbD approach in [4] and w.r.t. the velocity planner in [32] (which exploits a limited set of path-features), the proposed approach allows to improve the homogeneity of the deposition while adopting a simpler robot controller, and do not require manual demonstrations of the task (that are affected by teaching and recording errors/uncertainties). The proposed approach

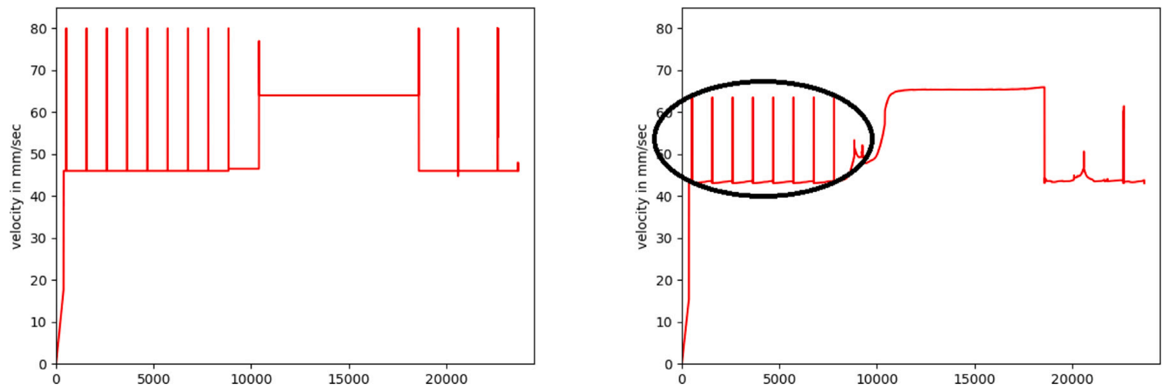

Fig. 8. Reference velocity for the not-optimized (left-side image) and for the optimized (right-side image) deposition task along the curvilinear axis of the deposition path. As it can be seen, the *Model-Based Process Reference* block plays a fundamental role in the optimization of the task performance, modulating the deposition task velocity to track the modeled optimal velocity while satisfying the task constraints (both including the human's knowledge-based constraints and the hardware constraints). As a matter of example, taking into consideration the initial part of the path (highlighted in black in Fig. 7 and in this Figure), it can be seen that the velocity along the horizontal part of this path is reduced (*i.e.*, the picks in the highlighted part of the velocity plot) in order to satisfy the acceleration limit. In the same way, the rest of the path is modulated in order to satisfy the optimization constraints.

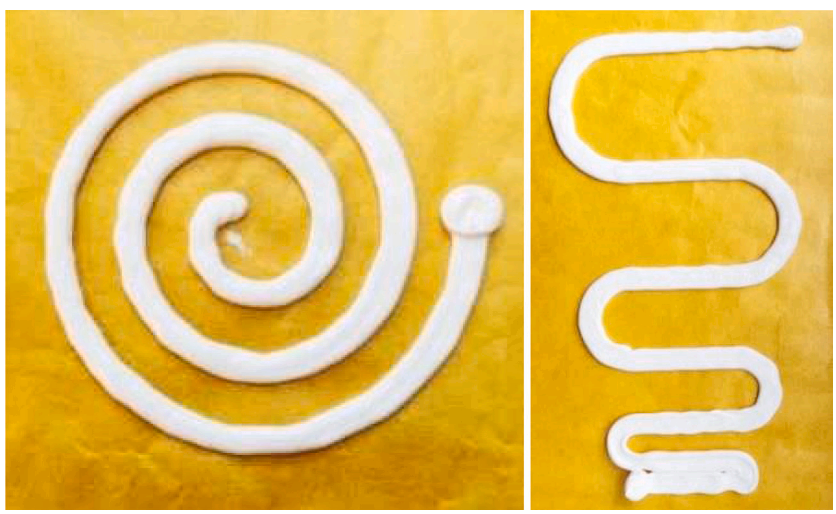

Fig. 9. Additional two deposition paths have been tested to show the generalization of the proposed human-centric process tuning approach.

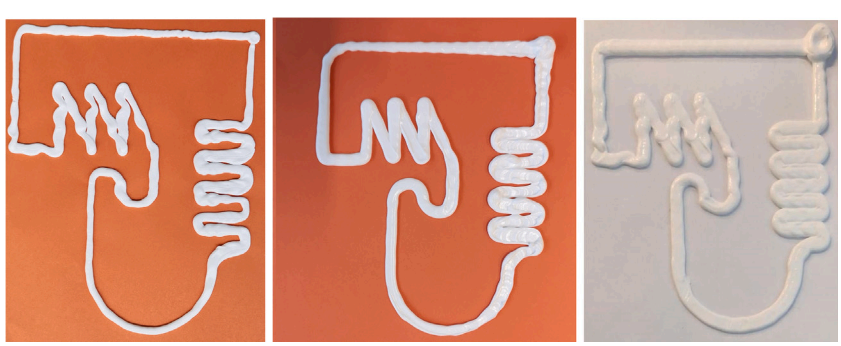

Fig. 10. Obtained deposition output exploiting the PbD approach in [4] (left-side image), exploiting the velocity planner in [32] (center of the image), and exploiting the proposed human-centric approach (right-side image). As it can be seen, the deposition output quality is improved in terms of homogeneity. The proposed approach is capable to embed human's knowledge into the simpler robot controller, providing improved generalization performance.

improves the generalization capabilities of the robotic system due to the extensive modeling of the process behavior, making it possible to catch the full operator's task knowledge.

Remark 6. It has to be noticed that the PBO (as the Bayesian optimization [34]) is not providing a purely converging behavior due to the exploration/exploitation behavior, based on the setting of the δ parameter in (8), as it is shown in Fig. 5. Indeed, an exit criterion can be defined based on the maximum number of optimization iterations or based on a target task output to be reached. More insights on the performance of the PBO in terms of optimal parameters computation and efficiency can be found in [27].

Remark 7. It has to be underlined that, in order to improve the generalization capabilities of the approach in [32], more path-features should be introduced. However, as it is shown in [32], this will increase the number of parameters to be tuned, increasing the complexity of the optimization process. The employed PBO performs efficiently with a maximum number of optimization parameters equal to 15. If more optimization parameters are defined, the optimization might not converge. Taking into consideration the approach in [32], 8 optimization parameters were already defined. Indeed, by adding a few more geometrical features (*i.e.*, 3 more) or increasing the modeling complexity of the ones already defined, the PBO limit is reached. The proposed human-centric approach, instead, reduces the optimization complexity while making it possible to model the human's process knowledge. In addition, the computational time of the PBO is minimized (less than 30 s for each optimization cycle), having only one optimization variable to be optimized (*i.e.*, the related deposition velocity) for each radius.

Remark 8. The proposed human-centric approach has been compared with the approach in [32] due to the fact that, to the best knowledge of the authors, no other work proposing a qualitative-based optimization framework is available. In addition, it has been compared with the PbD approach in [4] to show the improved capabilities of the proposed approach w.r.t. PbD methodologies. The proposed approach cannot be compared with quantitative-based optimization frameworks due to the specific focus on human-centric optimization not employing any measurement systems and/or quantitative performance indexes.

5. Conclusions

In this paper, a human-centric process tuning approach is proposed. Making use of preference-based optimization, the human's task knowledge is modeled. Additionally, information about the acceptability of the task performance are provided by the operator, being modeled and exploited as task constraints. Then, such models (together with other hardware constraints) are employed by an optimization algorithm to perform any general task maximizing the process output performance. The proposed approach has been validated on a robotic sealant material deposition task. The achieved results show the capabilities of the method to embed and exploit human's knowledge for process optimization purposes. Generalization capabilities are also demonstrated.

Future work will consider the modeling of the task constraints (*i.e.*, the acceleration in the considered deposition task) w.r.t. the task parameters (*i.e.*, of the path radius in the considered deposition task) to further improve the performance. In fact, in this way, it would be possible to improve the process modeling for optimization purposes. Indeed, due to its efficiency in terms of required experimental trials and fast performance judgment, the PBO will be employed in order to optimize the transition (and, therefore, the task-based constraints) between the task phases (*i.e.*, from one radius to the other in the considered deposition task). Furthermore, the online update (also exploiting the expert user's suggestions on the process parameters for further testing) of the modeled human's knowledge will be implemented to continuously improve such modeling. Additionally, the focus will be also moved to physical human—robot collaborative tasks, enhancing the human's knowledge modeling with a human's state modeling. In such a way, it will be possible to include in the global modeling the psycho-physical human's state (including, *e.g.*, the tiredness of the operator) to adapt the robot behavior to maximize the collaboration performance. Emotions monitoring will be also considered in order to map the sensations of the operator into the mentioned modeling.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Loris Roveda reports financial support was provided by Horizon 2020 and Hasler Stiftung.

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