Determining the Important Subjective Criteria in the Perception of Human-Like Robot Movements Using Virtual Reality

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This paper deals with the design and the evaluation of human-like robot movements. Three criteria were proposed and evaluated regarding their impact on the human-likeness of the robot movements: The inertia of the base, the inertia of the end-effector and the velocity profile. A specific tool was designed to generate different levels of anthropomorphism according to these three parameters. An industrial use case was designed to compare several robot movements. This use case was implemented with a virtual robot arm in a virtual environment, using virtual reality. A user study was conducted to determine what were the important criteria in the perception of human-like robot movements and what were their correlations with other notions such as safety and preference. The results showed that inertia on the end-effector was of most importance for a movement to be perceived as human-like and nonaggressive, and that those characteristics helped the users feel safer, less stressed and more willing to work with the robot.

Keywords: Human–robot interaction; robot movements; human-like movements; virtual reality.

1. Introduction

Human–robot interaction studies the way people and robots interact with each other. The interaction may be simple, like observing robots, being next to them or communicating with them. This interaction nowadays is becoming more complex,
especially with people and robots collaborating with each other on a daily basis in some industrial tasks. Human–robot collaboration, in the context of the industry, faces specific needs and challenges in terms of safety or efficiency. Since people and robots tend to be closer to each other and to work together, it is important to know how robots are perceived and accepted by people in their environment.

One important question is to know whether robots are better accepted if they behave like humans. Several factors have to be taken into account, such as robot appearance, robot movements or their overall interaction with people. In this paper, we focus on robot movements. Available studies in the literature lead us to better understand how to generate human-like robot movements using inverse dynamics, human motion imitation or with geometric constraints, but many questions remain unanswered. Because a human-like robot movement is sometimes hard to implement in real conditions, we propose to breakdown robot movements into multiple factors (three parameters will be proposed) and to study the effects of these parameters.

First, we are interested in determining the important criteria that make a robot movements human–like. Secondly, using these criteria, we want to know if human-like movements generated by our criteria are indeed better accepted by people, in terms of safety and the will to work with them. In this context, a specific tool was implemented to generate different levels of anthropomorphism on industrial robotic arms, and a user study was conducted to gather people’s subjective impressions.

In Sec. 2, we present related work on the generation of human-like movements and their perception on robots. In Sec. 3, we describe the tool that was implemented to generate human-like robot movements. Section 4 presents the use case, the different levels of anthropomorphism and the user study that was conducted. The results of this study are described in Sec. 5, before giving a short conclusion in Sec. 6.

2. Related Work on Robot Movements Evaluation

The study of the acceptability of human–robot interaction and collaboration has generally focused on several factors, which include robot appearance, robot movements, and more importantly anthropomorphism. Making a robot capable of acting as a human is a large field which involves developments of computationally-based representation, modeling, control, and animation of human movement.

Duffy defined anthropomorphism as “the tendency to attribute human characteristics to inanimate objects, animals and others with a view to helping us rationalize their actions”. Concerning robot appearance, the question is to know if a humanoid robot is better accepted than a machine-looking one: Mori asserted that it was true until a certain point was reached, when incomplete or awkward details were too disturbing. This phenomenon was called the uncanny valley, and several studies tried to confirm or discredit it. Psychological aspects were underlined in these studies showing, for example, the gap when humans start to attribute human-like cognitive processes to the robot. Concerning robot movements, the idea is to know if human-like movements are better perceived than machine-like ones.
It is not easy to determine what a human-like movement is. Several studies tried to highlight invariant characteristics of the human motion. Morasso studied point-to-point movements of the human hand and observed that the hand trajectories were always straight lines with a single peaked tangential velocity curve. Viviani and Terzuolo observed that, in the writing movements of the human hand, there was an invariant relation between the angular velocity and the curvature of the hand’s trajectory. Those invariants may be characteristics of a biological motion, and Johansson showed that the human visual perception was sensitive to those invariants: People were able to discern a biological motion described only by a few moving bright spots.

Even if invariants of the biological motion exist, it is another problem to model them. Many studies used their own human-like movements algorithms designed with a wide range of approaches. Some studies generated biological motion by minimizing the trajectory’s jerk, others by minimizing the torques’ rate of change. Additional studies also used the two-thirds power law to generate human-like movements. Finally, Taix et al. used a computational approach with optimal, Saab et al. used inverse dynamics, while Suleiman et al. used human motion capture.

The generation and perception of human-like movements on robots has been the focus of a lot of studies. Shibata and Inooka used an industrial robot with different velocity profiles to examine which factors were essential for human-likeness. Huber et al. compared two velocity profiles (trapezoidal joint and minimum-jerk) in a human-robot handing-over task, in terms of human-likeness and safety. Kulić and Croft and Zanchettin et al. estimated the human affective state in front of different robot motion strategies (human-like or not). Weistroffer et al. studied if the perception of human-like movements depended on the robot appearance. Another study showed that “the naturalness judgments did not completely indicate the perception of movement”. It was also shown that, for humanoid robots, rapid movements had a negative impact on naturalness. Co-verbal gestures have also been studied showing that nonverbal behaviors which affect anthropomorphism perception.

On the whole, those studies focused on specific robot movement profiles, determined how much they were perceived human-like and drew interesting results on their correlation with other notions, such as pleasantness, safety, or efficiency. But there were sparse details to explain which part of the motion was responsible for its human-likeness: Was it the end-effector trajectory, its speed or the overall structure of the movement? In this paper, we wanted to determine what were the important subjective criteria for an industrial robot’s movements to be perceived as human-like. We also wanted to know their correlations with other notions such as safety, competence and the will to work with them. In this context, different levels of anthropomorphic robot motions were generated, thanks to specific algorithms. An industrial use case was designed and a user study was conducted to gather subjective impressions on the different robot motions.
3. Human-Like Movements Generation

3.1. Inverse kinematics overview and techniques

To generate different robot arm movements for our study, Inverse Kinematics (IK) methods can be used. An IK problem can be explained as follows: In an articulated chain the generalized location of an end-effector $e$ (the joint at the end of a chain of joints) is a function of the rotations of all joints $\text{Joint}_i$ in that chain (see Fig. 1).

$$e = f(\text{Joint}).$$  
(1)

A typical IK problem is calculating these joints’ rotations using only the location of the end-effector: Given a desired position (Target), what must be the angles of the skeleton’s joints?

$$\text{Joint} = f^{-1}(\text{Target}).$$  
(2)

Equation (2) may not always have a (unique) solution. Indeed, there are multiple and sometimes endless combinations of joint degrees of freedom (DOF) values that put the end-effector in the right location. Van Welbergen et al.\textsuperscript{26} identified several numerical techniques to solve this problem: Analytical IK systems, Data-Based IK systems and Mesh-Based techniques.

Analytical IK systems, like the Jacobian Inverse method used in Refs. 27 and 28, use an iterative method that tries to approximate a good solution using the relation between the joint velocities and the velocity of the end-effector. The Cyclic Coordinate Descent (CCD) method proposed in Refs. 29 and 30 iterates through the joints, typically starting with the one closest to the end-effector and cycling through one joint variable at a time according to a heuristic.

Data-Based IK systems use motion data (motion capture or keyframe data) to automatically learn a model of logical and natural poses.\textsuperscript{31-34} The goal of this kind of systems is to generate the most natural poses: Poses that are most similar to the space of poses in the training data.

![Fig. 1. Example of an IK problem: Given the desired position of a skeleton’s hand (Target), what must be the angles of the skeleton’s joints?](image-url)
Finally, *Mesh-Based* IK techniques, like in Refs. 35 and 36, directly move the vertices and polygons of the three-dimensional (3D) model in order to deform the mesh toward the needed position.

### 3.2. *Spir.Ops* tool overview

In order to generate human-like movements for different robot arms, an IK system capable of generating believable movements is necessary and must be customizable enough to give the possibility to change anthropomorphic parameters based on the needed tests. Most off-the-shelf IK systems do not offer these possibilities. For our study, Spir.Ops\(^a\) created an anthropomorphic geometric-based IK system specific to our needs with a curve following tool to animate 6-DOF (Fig. 2(b)), 7-DOF (Fig. 2(a)) and 15-DOF (Fig. 2(c)) robot arms. Figure 3 shows the tool’s viewer.

### 3.3. Curve following

In Spir.Ops tool, we use cubic Hermite splines to represent the trajectories that each robot arm follows. A Hermite curve is a third-degree spline with each polynomial of the spline in Hermite form. The Hermite form consists of two control points and two control tangents for each polynomial. Hermite curves (Fig. 4) are used to smoothly interpolate data between key-points like object movement in keyframe animation or camera control. In our case, we use several Hermite curves to smoothly connect 3D waypoints to produce our final 3D trajectory.

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\(^a\)Spir.Ops is a private scientific research lab focused on artificial intelligence and procedural animation issues.
In order to travel our final 3D trajectory curve using a needed velocity (distance $d$ in Fig. 4), we sample each Hermite curve (300 sample in our case), and we use these samples as an approximation of each curve.

The velocity profile in our system can be either linear, or in the case of an anthropomorphic control we use the two-thirds power law to control this velocity.\textsuperscript{18} Two-thirds power law is an interesting property of the human hand curved

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(c) Robot with 15-DOF

Fig. 2. (Continued)

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Fig. 3. The viewer of the tool: Different robot structures can be managed.
movement stating that the speed $v$ of the hand movement on a curve is related to the curvature $c$ of the curve through a power law.

$$v = k \cdot c^{\frac{2}{3}}.$$  

Equation 3 is a two-thirds power law where $k$ is the velocity gain factor, accounting for differences in average movement velocity ($k = \frac{1}{3}$ in our system).

3.4. Anthropomorphic geometric-based IK system

As we are dealing with specific robot types (see Fig. 3), we created a specific geometric-based IK system that could be seen as less generic than off-the-shelf IK systems, but which at the same time is built around anthropomorphic modifiers which makes it powerful for the needed study.

Our system uses simple 3D geometric equations to find the joint angles of Eqs. (1) and (2). It is not iterative-based making it quite fast (performance wise): We calculate the needed angles for each Joint$_i$ directly without any try-and-error passes, as we will see later in this section.

First, we explain the used calculation steps and the anthropomorphic modifiers with the 7-DOF robot (see Fig. 2(a)). Then, we generalize to the other robots.

3.4.1. Basic steps

As all joints are aligned (no translation on the $x$-axis, Fig. 2(a)), we combine joints in 3 groups (see Fig. 5): Shoulder, Elbow, and Wrist (which contains the end-effector). We do so to simplify our geometric problem and to have a human-like arm structure.

The component Joint$_0$ of our robot shoulder is the one responsible for orienting the arm toward the target. We call the components Joint$_2$ and Joint$_4$, in the shoulder and in the wrist (respectively), the twist components. Joint$_6$ is a redundant twist used in case of an external constraint to make sure that the end-effector twist is
correct. Now, starting from the current robot arm position, the basic IK steps are the following:

- **Step-1:** Using the atan2 function, we calculate Joint$_0$ angle in order for the robot to face the needed target.
- **Step-2:** Using circles intersections equations (see Fig. 6), we calculate Joint$_1$ and Joint$_3$ values in order to place the Elbow joint Joint$_3$ on the selected intersection point.

With only these two steps, the end-effector points exactly at the needed target but: Some DOF (Joint) are not yet used and this robot animation is not yet customizable.

Fig. 5. The simplification used to help solving our IK problem.
3.4.2. Adding base inertia

In Step-1, our IK system calculates the final angle ($\theta_f$) in order for Joint$_0$ to face the target. This order is executed directly and the Joint$_0$ of the IK chain turns instantly.

To make the base joint movement smoother, with a more organic feeling, we added an inertia on Joint$_0$ movement using a spring damper. This inertia component adds a controlled delay when Joint$_0$ executes the commands of our IK system. In this way, Joint$_0$ converges toward the needed final angle $\theta_f$ in $t$ time based on the used spring damper regime (and not instantly). This changes our IK system as follows:

1. Our IK System calculates a $\theta_f$ for Joint$_0$ (Step-1).
2. The spring damper interpolates between current angle $\theta_c$ and $\theta_f$ based on its regime given us a $\theta_n$.
3. We apply this $\theta_n$ on our Joint$_0$.
4. In Step-2, the IK system starts with Joint$_0 = \theta_n$ now, so it calculates Joint$_2$ and Joint$_4$ values to compensate for this new delay, adding new twists on our animated chain.

In order to timely control the movement of this spring damper, we use the Settling Time $\tau_s$ principle, like in Abdul Karim et al.,$^{37}$ as follows: Let $m$ be a mass connected to a spring with stiffness constant $k$. This mass oscillates around a rest position $x_0$ with a viscous damper that has a damping coefficient $c$. Based on Newton’s second law of physics the acceleration is $\ddot{x} = -(k(x-x_0) + cx)/m$ where $x$ is the current position of the mass and $\dot{x}$ is its velocity. The mass $m$ oscillates around the rest value $x_0$, seeking to minimize the error $(x-x_0)$ until reaching zero. This oscillation depends

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Fig. 6. An example of the intersection circles used to calculate the needed Elbow position so the end-effector reaches the target.

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directly on the constants \((k, c, m)\). The Settling Time \(\tau_s\) is the time required for the mass position \(x\) to reach its maximum amplitude inside a given error interval (see Fig. 7) and remain inside it. This interval is symmetrical around \(x_0\).

\[
\tau_s = -\frac{\ln(\text{tolerance fraction})}{\zeta \times w_0}.
\]  

In Eq. (4), the tolerance fraction is the needed error interval shown in Fig. 7, \(w_0\) is the natural frequency and \(\zeta\) is the damping of the ordinary differential equation governing a damped harmonic oscillator:

\[
m\ddot{x} + c\dot{x} + k(x - x_0) = 0,
\]

or

\[
\ddot{x} + 2\zeta w_0 \dot{x} + w_0^2 (x - x_0) = 0,
\]

with

\[
\zeta = \frac{c}{2mw_0}, \quad w_0 = \sqrt{\frac{k}{m}}.
\]

By fixing the tolerance fraction to 5\% in Eq. (4) and by using the user provided settling time and damping (underdamped most of the time with a value of 0.7), the spring damper constants \(k\) and \(c\) are calculated from Eq. (5), achieving total control over the curve of the spring damper while maintaining its dynamic aspect.

Even with the addition of the Base Inertia, the resulting wrist movement is still static (Joint5 is not animated yet) and the wrist only reacts to the base joint delay if it is active (the calculated twist on Joint4). It is like if the movement is driven by the base Joint0, while, normally, the wrist (with the end-effector) is the most important component and the one that should be driving the whole articulated chain motion toward the target. So first, we add the ability to control the wrist Joint5 angle.
independently as illustrated in Fig. 6. We go through the previous IK steps as before (Fig. 8(a), then we affect the needed Joint5 angle (Fig. 8(b)) and finally, we adapt Joint1 and Joint3 to the new circle using the same circles intersections equations in Step-2 as illustrated in Fig. 8(c).

3.4.3. Adding end-effector inertia (Whip Effect)

The idea behind this effect is to add an intelligent control on the previous wrist movement (Joint5), between a mechanical mode and an anthropomorphic mode. In
the mechanical mode (left column in Fig. 9), the end-effector is the driving force of the movement. This seems normal as the sole objective of the robot arm movement is to make sure that the tool (the end-effector) achieves the target. At the same time, in the mechanical mode, the IK system tries to make the minimum possible movement
(moving the joints as minimum as possible) in order to simulate a robot that is looking for energy efficiency. In this mode, the robot tries to only move its wrist Joint$_5$ to achieve the target and the IK system adapts to this new wrist position. Only when the relative angle Joint$_5$ reaches a certain limit the rest of the joints start being more active and follows the end-effector.

In the anthropomorphic mode, we add an end-effector inertia (Whip Effect): We apply a virtual force on the wrist in the direction of the end-effector movement.
While we ensure that the end-effector reaches the target, we add an inertia component to the wrist making it the driving component of the movement. This effect can be observed when watching the wrist-brush movement of a painter or the movement of the wrist-equivalent joint in animals when running. We call it the **Whip Effect** because it resembles the wrist/whip movement when someone slings a whip: The tip of the whip is always in delay behind the rest of the whip until it reaches the target. And as we are going to see in this study, this movement is quite important when humans perceive the robot movement.

To add this effect, we calculate an angle $\theta_w$ based on the arm movement direction and we use a spring damper (the same type as before) to smooth this angle, given us a $\theta_{w2}$ that we apply on Joint5 (see Fig. 9 right column).

When the robot arm stops moving, the spring damper converges to its rest state giving us the positions in Figs. 10(c) and 10(f).

Both robotic and anthropomorphic wrist effects work in 3D by using 2 spring dampers: One on the pitch component of the movement affecting Joint5 directly and a second one on the roll component of the movement affecting Joint4 directly (see Fig. 11).

### 3.4.4. Robots generalization

Finally, we generalize this IK system on the other robots as follows:

1. The 6-DOF robot can be seen as the same as the 7-DOF without Joint2 of the 7-DOF robot.
2. The 15-DOF robot is two 7-DOF arms with a common base Joint0 that always tries to face the middle point of both arms target. We apply the **Base Inertia** on this joint.

![Added effects on the Wrist in 3D](image)

(a) Without Whip Effect  (b) With Whip Effect

Fig. 11. Added effects on the Wrist in 3D.
4. User Study

4.1. Aim of the study

The aim of the study was to observe and compare different robot movements, to determine which criteria were perceived as human-like and to determine their correlation with other notions such as safety. In this context, a use case was chosen in which an industrial robot arm had to work on a car door according to different movement conditions. A within-subject study was performed with a diverse population: The users had to observe each movement condition and to give their feelings by answering a questionnaire.

4.2. Use case

The industrial use case we studied was a car door assembly. One important operation in this use case is the setting of a sealing sheet. This operation currently requires the operator to put a sealing sheet on the door, to ensure it is well positioned and to definitely stick it to the door by rolling a caster on the edges.

In our situation, an industrial robot arm (7-DOF Motoman SIA10 robot) was imagined to apply the caster on the edges of the sheet. The robot’s end-effector travelled along its trajectory (the edges of the sheet) at about 0.4 m/s (see Fig. 12). The robot also had to stop at two specific points of the trajectory, since interesting behaviors (like inertia) may appear when the movement is stopped. The robot was performing its task in an infinite loop, to give time to the users to observe it.

![Fig. 12. The industrial use case: The setting of the sealing sheet.](image-url)
4.3. Robot movements

The movements of the robot could vary depending on three main parameters, controlled by the tool described in Sec. 3. Table 1 shows details concerning these parameters. Parameter $P_1$ controlled the inertia on the robot’s base, resulting in a delay between the base and the first segment of the robot. Parameter $P_2$ controlled the inertia on the end-effector. Parameter $P_3$ was used to modify the velocity profile (linear or two-thirds power law). Those parameters were inspired by biomechanics and chosen based on Spir.Ops experience in IK Systems. They were used to generate movements that were natural and plausible on robot arms, and were sufficient for our study. They were simple to use and allowed us to generate a large panel of movements that were quite different.

Given these three parameters, eight different types of robot movements were generated depending on the activation of each parameter. A reference movement (the other movements had to be compared to this one) was also designated, with all parameters deactivated. Table 2 shows the name of each robot condition and their corresponding parameter activation.

4.4. Experimental setup

The use case was implemented in a virtual environment using virtual reality. 3D models of the industrial environment were used: A car door, an assembly line and a robot. The virtual environment was rendered on a back-projected wall

<table>
<thead>
<tr>
<th>Parameters</th>
<th>ON</th>
<th>OFF</th>
</tr>
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<tbody>
<tr>
<td>$P_1$ Inertia on the base</td>
<td>1.5 s</td>
<td>0.05 s</td>
</tr>
<tr>
<td>$P_2$ Inertia on the end-effector</td>
<td>roll = 15</td>
<td>roll = 0</td>
</tr>
<tr>
<td></td>
<td>pitch = 30</td>
<td>pitch = 0</td>
</tr>
<tr>
<td>$P_3$ Velocity profile</td>
<td>Two-thirds power law</td>
<td>Linear</td>
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</table>

<table>
<thead>
<tr>
<th>Robots</th>
<th>$P_1$</th>
<th>$P_2$</th>
<th>$P_3$</th>
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<tbody>
<tr>
<td>$R_{ref}$</td>
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<td>OFF</td>
<td>OFF</td>
</tr>
<tr>
<td>$R_0$</td>
<td>OFF</td>
<td>OFF</td>
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</tr>
<tr>
<td>$R_1$</td>
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<td>$R_2$</td>
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<td>$R_3$</td>
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<tr>
<td>$R_7$</td>
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</tr>
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(3.1 m × 1.7 m) with active stereoscopy. ART cameras were used to track the head of the users (see Fig. 13).

4.5. User study protocol

The user test was conducted as follows. Each robot had to be compared with the reference one. Before each condition, \( R_{\text{ref}} \) was first shown to the users. When the participants had sufficiently observed the reference robot, the test robot was presented to them and \( R_{\text{ref}} \) disappeared. The participants took their time to perceive differences with the reference then said to the coordinator when they were ready to answer the questionnaire. After answering the questions, the reference robot was shown again and the test went on with the next robot movement.

The questionnaire is shown in Table 3. For each question, a 7-point Likert scale was used: The participants had to give a grade relative to the reference robot, between \(-3\) and \(+3\). If a difference was perceived in a negative manner, a negative grade could be given \((-3, -2, -1)\); if a difference was perceived in a positive manner, a positive grade could be given \((1, 2, 3)\); if no difference was perceived, a neutral grade could be given \((0)\). The questionnaire was written with the help of a person from ergonomics. The construct validity of the questionnaire was, however, not checked.

The order of robot movements was randomized for each participant. Moreover, three occurrences of robot \( R_0 \) (identical to \( R_{\text{ref}} \)) were presented \((R_{01} \text{ being the first apparition, } R_{02} \text{ the second one and } R_{03} \text{ the last one})\), so that there were actually
10 robot conditions ($R_{01}$, $R_{02}$, $R_{03}$, $R_1$, $R_2$, $R_3$, $R_4$, $R_5$, $R_6$, $R_7$). The three robots $R_0$ were strictly identical to the reference $R_{\text{ref}}$. Each participant was aware of the fact that a robot could be identical to the reference but they did not know when such a robot appeared. The test stopped when all the robot conditions had been seen by the participant. The duration of the experiment for each subject was about 30 min.

4.6. Population

A total of 39 subjects participated in this study. The average age was 35.2 with a median of 31. There were 17 men and 22 women with a wide variety of working fields and study level (from no degree to Ph.D.). None of them were familiar with robots.

5. Results

In this section, we show and analyze the results of the questionnaire. First, we present an overview of the results by performing a comparison between movement parameters. Then, we propose an interpretation of the results of this comparison. Finally, we present the overall detailed results of the questionnaire, by notions and over all the robots.

5.1. Parameter comparison

In order to determine which parameters were responsible for the robot’s humanlikeness and other notions of the questionnaire, robots were grouped depending on their parameters. For each parameter ($P_1$, $P_2$, $P_3$), two groups were made: The robot conditions activating the corresponding parameter and the ones not activating it. Figures 14(a), 14(b) and 15 show the average answers to the questionnaire for each subgroup of each parameter. Wilcoxon tests were performed to determine significant differences between subgroups. For robot $R_0$, only the last occurrence $R_{03}$ was taken into account.
As can be seen in Fig. 14(b), parameter $P_2$ seems to have the most influence in the perception of robot movements. Indeed, no significant difference was found between subgroups for parameter $P_3$ (Fig. 15), meaning that velocity profile was of little impact. Significant differences were found for $P_1$ only for flexibility, mechanicality and predictability (Fig. 14(a)), while for $P_2$ significant differences were found for every notion of the questionnaire, except competence, speed, and stress. This shows that the important parameters in the perception of robot movements are, in decreasing importance order, $P_2$, $P_1$ and then $P_3$. 

As can be seen in Fig. 14(b), parameter $P_2$ seems to have the most influence in the perception of robot movements. Indeed, no significant difference was found between subgroups for parameter $P_3$ (Fig. 15), meaning that velocity profile was of little impact. Significant differences were found for $P_1$ only for flexibility, mechanicality and predictability (Fig. 14(a)), while for $P_2$ significant differences were found for every notion of the questionnaire, except competence, speed, and stress. This shows that the important parameters in the perception of robot movements are, in decreasing importance order, $P_2$, $P_1$ and then $P_3$. 

Fig. 14. Results depending on $P_1$ and $P_2$ activated or not.

Fig. 15. Results depending on $P_3$ activated or not.
In order to study the interaction effects between parameters, we conducted an additional analysis. The aim of this analysis was to evaluate whether the influence of a specific parameter \( P_1 \), \( P_2 \), or \( P_3 \) depended on the states of the other parameters (activated or not). In the following, we define the influence of a specific parameter \( P_i \) as the difference \( \Delta P_i \) in grades between a robot having \( P_i \) activated and the same robot having \( P_i \) deactivated (see Table 4 for the calculations with parameter \( P_1 \)). Having significant different values of \( \Delta P_i \) when another parameter \( P_j \) is activated and when \( P_j \) is deactivated shows that there is a significant interaction effect between \( P_i \) and \( P_j \). Wilcoxon pairwise tests were performed to compare each category and assess significant differences.

The results showed no significant interaction effect between parameters \( P_1 \) and \( P_3 \) and between parameters \( P_2 \) and \( P_3 \). This is mainly due to the already nonexistent influence of parameter \( P_3 \) on the results. However, a significant interaction effect was shown between \( P_1 \) and \( P_2 \), for all notions except competence, speed, predictability and work situation. Figure 16(a) shows the comparison of results for \( \Delta P_1 \) when \( P_2 \) is

![Graph](image1.png)

(a) Values of \( \Delta P_1 \) depending on \( P_2 \)

![Graph](image2.png)

(b) Values of \( \Delta P_2 \) depending on \( P_1 \)

Fig. 16. Influences of parameters \( P_1 \) and \( P_2 \) (\( \Delta P_1 \) and \( \Delta P_2 \)) depending on the other parameter’s state.
activated and deactivated, while Fig. 16(b) shows the comparison of results for $\Delta P_2$ when $P_1$ is activated and deactivated.

In Fig. 16(a), we can clearly see that the influence of parameter $P_1$ ($\Delta P_1$) was different depending on if $P_2$ was activated or not. The difference is mostly qualitative: While a certain trend for $\Delta P_1$ was shown when $P_2$ was deactivated, the opposite trend was shown when $P_2$ was activated. On the whole, the influence of $P_1$ was more positive when $P_2$ was deactivated, and the influence of $P_1$ became negative when $P_2$ was activated. For example, for aggressiveness, a positive influence of $P_1$ was shown when $P_2$ was deactivated ($\Delta P_1 < 0$, less aggressiveness was found), while the opposite trend appeared when $P_2$ was activated ($\Delta P_1 > 0$, more aggressiveness was found). Similar trends may be observed with the other notions of the questionnaire.

Significant differences were also found for $\Delta P_2$ depending on the activation of $P_1$, but these differences were mostly quantitative (and not qualitative, see Fig. 16(b)). Indeed, the same trends were always observed for the influence of $P_2$ (positive influence), but with different amplitudes depending on the activation of $P_1$. The positive influence of $P_2$ was always more important when $P_1$ was deactivated than when $P_1$ was activated. This effect seems understandable: The influence of $P_2$ could be more clearly observed when there were no other parameters activated. When $P_1$ was activated, the movements were already perceived as more natural, thus decreasing the influence of $P_2$.

The analysis of the interaction effects shows that the results are always better when $P_2$ is activated. However, an interaction effect exists between $P_1$ and $P_2$ and shows that it may not be a good solution to have both $P_1$ and $P_2$ activated at the same time: The influence of $P_1$ would then be perceived in a negative way. Figure 17
shows the absolute results for four subgroups of robots: The ones having neither $P_1$ nor $P_2$ activated, the ones having only $P_1$ activated, the ones having only $P_2$ activated and the ones having both $P_1$ and $P_2$ activated. In this figure, we can clearly see that $P_2$ was responsible for the main differences in the perception of robot movements: Having $P_2$ alone activated was often an asset for a movement to be perceived as human-like and safe, while $P_1$ was of much more negligible or negative impact.

5.2. Overall interpretation

5.2.1. Robot characteristics

Three characteristics seemed to be common to the robots with $P_2$ activated (with $P_1$ or not): Flexibility, naturality and mechanicality. Indeed, for all three notions, those robots got the best grades. This shows that inertia on the end-effector of the robot was perceived as a mark of flexibility, and that a flexible robot was seen as more natural and less mechanical.

Moreover, three other characteristics were common only to the robots with $P_2$ alone activated: Human-likeness, aggressiveness and relaxation. For those notions, robots with only $P_2$ activated got better results than the robots with both $P_1$ and $P_2$ activated. The inertia of the end-effector was perceived as less aggressive (thus more relaxing) and more human-like, but it was the case only if $P_1$ was deactivated: Having both inertia on the base and on the end-effector was more negative than having inertia on the end-effector only.

Finally, robots with only $P_2$ activated were perceived as less predictable than the ones with $P_1$ activated. The inertia on the root implied more predictability: This can explain why it was perceived as less human-like and more aggressive.

5.2.2. Users' feelings

Regarding the last four notions on the users' feelings (safety, preference, stress, and work situation), robots with only $P_2$ activated always got the best results. The characteristics of flexibility and naturality could be used to explain this trend, but this would not explain the differences with the robots with both $P_1$ and $P_2$ activated. Therefore, it is the notions of human-likeness and aggressiveness that can explain this trend. Since the movements with $P_2$ alone activated were perceived as the least aggressive and the most relaxing, it is understandable that they induced less stress and more safety. Human-likeness also played a role in the users' feelings, especially to explain their preference and their will to work next to them.

5.3. Results description with all the robots

This section presents the results of the questionnaire, for each robot instead of each parameter. The aim is not to give a further analysis of the results: The main detailed analysis was given in Sec. 5.1, by comparing parameters. The aim is rather to give the detailed answers to the questionnaire and to illustrate the analysis from Sec. 5.1 by
describing the results with an overview of all the robots. Figures 18–24 present the results of every notion of the questionnaire with each robot.

First, we can clearly observe that robots $R_{01}$, $R_{02}$ and $R_{03}$ were perceived close to the reference robot. This reflects that participants were clearly able to detect that a robot was similar to the reference, thus validating that they did not answer at random.

The relative importance of each parameter ($P_1$, $P_2$, $P_3$) may be observed by simply comparing robots $R_1$, $R_2$, and $R_3$. $R_3$ was always rated close to the reference,
illustrating a low influence of parameter $P_3$, while $R_2$ always had the best results, illustrating a major influence of parameter $P_2$ compared to $P_1$.

It was shown in Sec. 5.1 that parameter $P_3$ had very little impact on the results of the questionnaire and on the other parameters. This can be observed in Figs. 18–24 by comparing robots and by forming pairs: $R_0$ and $R_3$, $R_1$ and $R_6$, $R_2$ and $R_5$, $R_4$ and $R_7$. Each of these pairs contain the same two robots, with or without $P_3$ activated. It is interesting to observe, for each notion of the questionnaire, that the two robots of

![Graph](image1)

(a) Relaxing–soothing notion

![Graph](image2)

(b) Flexible–tough notion

Fig. 20. Results of the relaxation and flexibility notions.

![Graph](image3)

(a) Fast–slow notion

![Graph](image4)

(b) Mechanical–nonmechanical notion

Fig. 21. Results of the speed and mechanical notions.
each pair were very often rated the same. This illustrates that parameter $P_3$ had little influence on the results.

Finally, it was also shown in Sec. 5.1 that parameter $P_2$ had the most influence on the results, but that it interacted with parameter $P_1$. The conclusion was that, to improve the user’s feelings, it was better to activate $P_2$ alone rather than having both $P_1$ and $P_2$ activated. This conclusion may be observed in Figs. 18–24. Indeed, the pair of robots $R_2-R_5$ had very often the best grades: This pair correspond to the robots having $P_2$ activated (but not $P_1$). The second pair of robots which had good

![Fig. 22. Results of the predictability and safety notions.](image)

![Fig. 23. Results of the preference and stress notions.](image)

Determining the Important Subjective Criteria
results (as good as or lower than the pair $R_2 - R_5$) in the questionnaire is the pair $R_4 - R_7$: This pair correspond to the robots having both $P_1$ and $P_2$ activated. Finally, the pair $R_1 - R_6$ correspond to the robots having $P_1$ activated (and not $P_2$) and always got lower results. This observation illustrates the conclusions given in Sec. 5.1. In the overall results shown in Figs. 18–24, we can observe that robot $R_3$ was approximately noted as the reference (notes are close to 0). This observation leads us to say that $R_2$ and $P_3$ had the greatest influence on this notion.

6. Conclusion

In this paper, the focus was to study the perception of robot movements. We were interested in evaluating what made robot movements human-like and in assessing people subjective opinions about it. In this context, different levels of anthropomorphic robot movements were generated thanks to an anthropomorphic IK system. A user study was conducted to compare several movements and gather subjective impressions about them. This user study relied on an industrial use case: An industrial robot arm had to perform a task on a car door in the context of an assembly line. This use case was implemented using virtual reality with a virtual robot. Questionnaires were given to the users to assess their impressions.

The results showed that the most important criterion of the robot movement was the inertia on the end-effector. Additionally to being perceived as more flexible and more natural, the inertia on the end-effector was also necessary for the movement to be perceived as more human-like and less aggressive. A further analysis showed that those two characteristics (human-likeness and aggressiveness) were essential in the users’ feelings: A human-like and nonaggressive robot movement helped the users feel safer, less stressed and more willing to work with the robot.
These results may be used to design new robot movements that are better perceived by users in their environment. However, some care must be taken when analyzing our study. First, we did not check the construct validity of our questionnaire: This is a limitation of our study and we will focus on this issue for future studies. Secondly, our study was performed with a virtual robot: Results may change when dealing with a physical robot, especially concerning safety. Finally, the context of our study was a robot working on an industrial assembly line: Results should be extended to other situations (homecare robots for example) with caution. Imposing inertia on the robot end-effector may not always be possible, in cases where it has to keep a specific orientation. In spite of those remarks, we believe that our study improved the overall knowledge on the perception of robot movements.

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References

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