A Novel Metrics for the Quantification of the Agent's Affordance: A Preliminary Study

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Abstract. In multiple research fields (ergonomics, product design, robotics), many studies aim to express the different types of agent-environment interactions through the concept of affordance. Nevertheless, a standardized metrics able to quantify the affordance is still absent, or limited to specific applications, lacking in generalization. In the present article authors propose a novel metrics able to quantify the agent-environment interaction in a continuous scale (affordance level), through an information-based measure. To quantify the agent-environment interaction, the motor difficulty of the observed agent is compared to the motor difficulty of a reference agent whose movements allow to successfully execute the motor task. The proposed metrics expresses the ability of an observed agent in accomplishing a motor task (agent-environment interaction) by capturing its stochastic behavior. The quantitative metrics for the affordance has great potentials in different fields of application since it can be applied to any motor task. Results of simulations performed show the effectiveness of the metrics, paving the way to a range of new applications and promising research directions.

Keywords: Affordance, Motor Task, Quantitative Metrics.

1 Background

In the Ecological Psychology research field, Gibson coined the term 'affordance' to express how an animal perceives the surroundings, underlying the action possibilities enabled by the environment [1]. Due to the multiple formulations and the various research fields where the affordance has been used (ergonomics, industrial design, and robotics), the term 'animal' has been substituted by 'agent', a general term that represents the subject (animal, robot, human, co-bot) of the interaction with the environment. Ecological psychologists deepened the affordance meaning, claiming that it can be a property of the agent-environment system [2], or a relation between abilities of the agent and features of the environment [3]. In industrial design Norman com-

bined the affordance with notions from ergonomics: he discerned between the 'actual' and 'perceived' affordance, referring to the first as the real functionality of the object, and to the latter as the functionality of the object perceived by the agent [4]. In robotics, researchers adopted the affordance to increase perceptual capabilities of robots in interacting with the environment [5], [6]. The potential actions of robots in the environment (navigation, manipulation, grasping objects, locomotion) are evaluated basing not only on geometric features of the surroundings, by focusing on what is afforded: the robot evaluates if an object is 'graspable' or 'rollable', or if a path is 'walkable', instead of focusing only on identities of the surroundings (shape, color…). Despite the widespread adoption of affordance, current models do not evaluate the agent-environment interaction through a quantitative metrics independent from the research field or task considered. Warren [7] executed experiments to evaluate the agent's affordance in stair climbing, identified as the ratio between the leg length (the agent) and stair height (the environment): when the ratio is greater than 0.88 (critical point), the stair cannot be climbed. Despite this quantitative result, the ratio is a body-scaled measure and do not take into account non-anthropometric features that could affect the stair climbing (e.g., age): in many cases the action possibilities are related not only on body-scaled measures [8]. Furthermore, this result could be applied only for stair climbing applications, through a binary approach (yes/no affordance).
For these reasons, in the present article a novel quantitative metrics independent from the application field, able to evaluate the agent's affordance in a continuous scale and considering both agent-related and environment-related features, is proposed.
The remaining of this paper is organized as follows: the second section is devoted to the description of the quantitative metrics able to evaluate the agent's affordance level by focusing on both the reference and observed agent; the third section is devoted to the analysis of results obtained from the numerical simulation. In the last section conclusions are provided.

2 Material and Methods

The quantitative metrics able to express the agent's affordance level is evaluated through an information-based measure called Index of Difficulty (ID). The original ID defined by Fitts, aimed at quantifying the difficulty of a simple reaching motor task characterized by a target of width W, placed at distance D from a given starting point [9]. Other authors extended the application of the ID, to express the difficulty associated to a motor task characterized by a general trajectory t, fully constrained by a target of width $W(s)$ orthogonal to the trajectory t at the curvilinear coordinate s [10].

$$\boldsymbol{ID} = \int_{\boldsymbol{t}} \frac{\boldsymbol{ds}}{\boldsymbol{W(s)}} \tag{1}$$

In [11] equation (1) has been modified to evaluate the motor difficulty of an observed agent in performing a general motor task (walking) by considering the stochastic behavior of the agent through trajectories executed ($t_k, k = 1, \dots, n$) and movement variability $W(s, \varphi)$:

$$ID_{agent}(t_{avg}, \varphi) = \int_{t_{avg}} \frac{ds}{W(s, \varphi)} \quad (2)$$

Where t_{avg} is the average trajectory, and $W(s, \varphi)$ is evaluated in the section orthogonal to t_{avg} at the curvilinear coordinate s (Fig. 1). Since in reaching motor tasks agent's trajectories are normally distributed with respect to their average t_{avg} [12], [13], it is assumed that spatial configurations (i.e. action possibilities) reached at s ($q_k(s)$) follow a Gaussian distribution centred in t_{avg} ($q_{avg}(s)$), with a probability level φ.

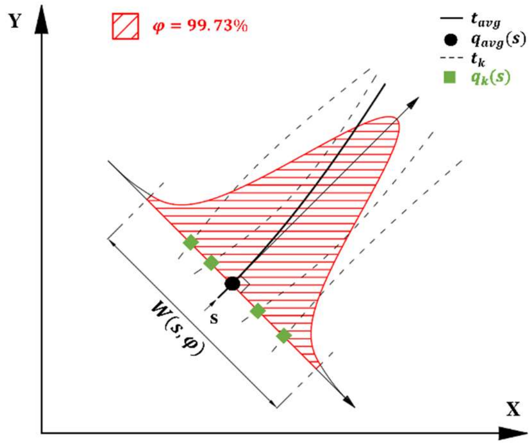

Fig. 1 Distribution of $q_k(s)$ at s

$W(s, \varphi)$ is evaluated as:

$$W(s, \varphi) = 2 \cdot \bar{z} \cdot \sigma(q_k(s)) \quad (3)$$

Where $\bar{z}$ is the z-score ($\bar{z} = 3$ for $\varphi = 99.73\%$) and $\sigma(q_k(s))$ is standard deviation of $q_k(s)$. $W(s, \varphi)$ expresses the action possibilities of the agent in interacting with the environment: greater the extent of $W(s, \varphi)$, more the alternatives available to the agent to execute the motor task. In this context no reference is provided on how the motor task should properly be executed. This information will be included in case of a reference agent, whose movements show how the motor task should be optimally performed.

In the following subsections, equation (2) will be adopted to evaluate the motor difficulty of both the reference and observed agent.

2.1 Reference Agent

In general motor tasks, a nominal trajectory (t_{ref}) to follow can be defined for multiple reasons: it can represent the best path allowing to successfully execute the task (under spatial or time constraints), or in case of robots, it can represent the trajectory allowing to minimize the agent's cost function (e.g. minimum jerk) for a high-level motor coordination. Unfortunately, agents cannot perfectly follow the nominal trajectory, since movements are generated by a noisy system [14], [15]. Consequently, it can be defined a given width $W_{ref}(s)$ centered in t_{ref} and orthogonal to t_{ref} at the curvilinear coordinate s, expressing the maximum tolerance of movement variability allowing to successfully execute the task. By considering both $W_{ref}(s)$ and t_{ref}, the optimal behavior in performing a general motor task is expressed through the motor difficulty of the reference agent, defined as:

$$\boldsymbol{ID_{ref}} = \int_{t_{ref}} \frac{\boldsymbol{ds}}{\boldsymbol{W_{ref}(s)}} \tag{4}$$

Briefly, $W_{ref}(s)$ represents the region of allowable action possibilities to correctly execute the task. As said before, in reaching motor tasks agent's trajectories are normally distributed: consequently, movements of a reference agent are assumed to follow a Gaussian distribution centered on $q_{ref}(s)$, point of t_{ref} at the curvilinear coordinate s, at a given probability $p_{ref}(s)$ (Fig. 2). $f_{ref}(s,x)$ is the probability density function of the distribution at s. $p_{ref}(s)$ and $f_{ref}(s,x)$ are constant along the t_{avg}.

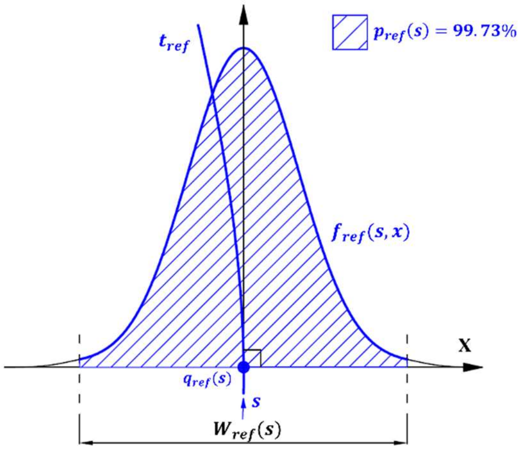

Fig. 2 Reference Agent's behaviour ($f_{ref}(x)$) at s

The assumption that frequencies of spatial configurations reachable by the reference agent are normally distributed in the section orthogonal to t_{ref}, represents the best behaviour achievable, since the higher frequency is defined on $q_{ref}(s)$: the observed agent should follow this behaviour along the entire path to optimally execute the task. Both $W_{ref}(s)$ and t_{ref} can be chosen during the design phase of the motor task, defining the maximum allowable tolerance, and the nominal trajectory to follow to optimally execute the task. In this case $W_{ref}(s)$ is defined a priori, and from (3) it is possible to evaluate the standard deviation of the spatial configurations reachable by the reference agent $\sigma_{ref}(s)$ as:

$$\boldsymbol{\sigma_{ref}(s)} = \frac{\boldsymbol{W_{ref}(s)}}{\boldsymbol{2 \cdot \bar{z}}} \tag{5}$$

$p_{ref}(s) = 99.73\%$, with $\bar{z} = 3$, for each curvilinear coordinate s (i.e., $p_{ref}(s) = p_{ref}\ \forall\, s$). On the other hand, t_{ref} and $W_{ref}(s)$ can also refer to a real agent whose movements allow to successfully execute the task such as to consider its behaviour as a reference.

2.2 Observed Agent

Movements executed by the observed agent should be as close as possible to the ones of the reference agent: greater the similarity between the two behaviors, higher the affordance level. In fact, by defining the behavior of the reference agent through the t_{ref} and $W_{ref}(s)$, it is possible to quantify the agent-environment interaction, i.e. the effectiveness of the observed agent in executing the motor task.
For a perfect matching between the two agents' behaviors, the motor difficulty experienced by the observed agent must be equal to ID_{ref}: in this case the action possibilities of the observed agent (i.e., spatial configurations reachable) fit perfectly with the action possibilities of the reference one.
The motor difficulty of the observed agent is evaluated relative to the reference movements that should be performed while executing the motor task:

$$\boldsymbol{ID}_{\cap} = \int_{t_{avg}} \frac{\boldsymbol{ds}}{\widetilde{\boldsymbol{W}}_{\cap}(\boldsymbol{s})} \tag{6}$$

t_{avg} is the average trajectory, while $\widetilde{W}_{\cap}(s)$ is defined as:

$$\widetilde{\boldsymbol{W}}_{\cap}(\boldsymbol{s}) = \boldsymbol{W}_{\cap}(\boldsymbol{s}) \cdot \boldsymbol{p}_{\cap}(\boldsymbol{s}) \cdot \boldsymbol{\eta}_{\cap}(\boldsymbol{s}) \tag{7}$$

$\widetilde{W}_{\cap}(s)$ is indicative of the observed agent's behavior, evaluated in the section orthogonal to t_{ref} (nominal trajectory) at the curvilinear coordinate s. $W_{\cap}(s)$ represents the region where spatial configurations reachable by the observed agent are within $W_{ref}(s)$ ($W_{\cap}(s) \leq W_{ref}(s)$): it provides 'extensive' information on action possibilities reachable within the reference tolerance. $W_{\cap}(s)$ can be lower than $W_{ref}(s)$ when the observed agent is physically constrained, unable to reach all the spatial configurations within the reference tolerance: lower the $W_{\cap}(s)$, greater the difference with the reference agent. In Fig. 3 the case of $W_{\cap}(s) = W_{ref}(s)$ is shown.

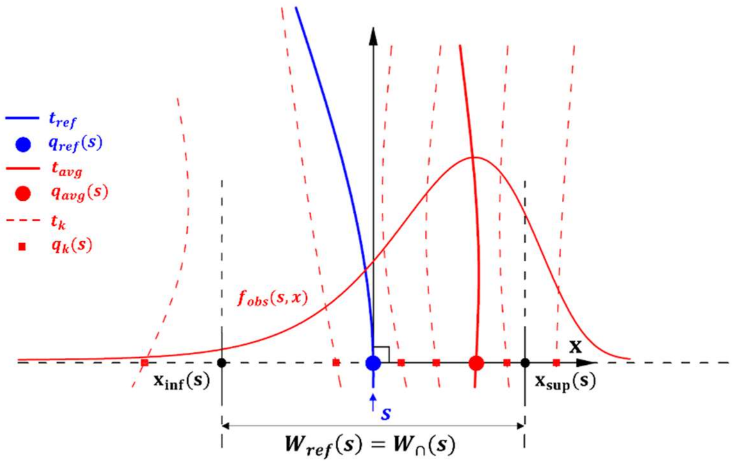

Fig. 3 Example of the Observed Agent's behaviour ($f_{obs}(s,x)$) at s

From spatial configurations (i.e. action possibilities) reached at s ($q_k(s)$), the corresponding probability density function $f_{obs}(s,x)$ can be obtained.
Due to the stochastic nature of agents, the behavior of the observed agent will be never the same as the reference one. Differences between the two behaviors are identified by two factors: $p_\cap(s)$ and $\eta_\cap(s)$.
$p_\cap(s)$ quantifies the probability of the observed agent in reaching spatial configurations within $W_{ref}(s)$. $p_\cap(s)$ is evaluated from the probability density function $f_{obs}(s,x)$, between the boundaries of $W_{ref}(s)$ ($x_{inf}(s)$ and $x_{sup}(s)$):

$$\boldsymbol{p_\cap(s) = \int_{x_{inf}(s)}^{x_{sup}(s)} f_{obs}(s,x)dx} \tag{8}$$

When $p_\cap(s) = p_{ref}(s) = p_{ref}$, all the spatial configurations reachable by the observed agent are within $W_{ref}(s)$. Nevertheless, this is not enough to state that there is a perfect matching between the two agents' behaviours. $p_\cap(s)$ provides us 'quantitative' information on action possibilities, but nothing is said about their frequency distribution within $W_{ref}(s)$ (i.e., 'qualitative' information).
$\eta_\cap(s)$, called 'overlapping index' [16], allows to evaluate the similarity between two probability distribution functions, in this context referrable to $f_{ref}(s,x)$ and $f_{obs}(s,x)$:

$$\boldsymbol{\eta_\cap(s) = \int_{x_{inf}(s)}^{x_{sup}(s)} \min\,[f_{ref}(s,x), f_{obs}(s,x)]dx} \tag{9}$$

$\eta_\cap(s)$ is evaluated by considering the minimum between the two pdf and by applying the integral between the boundaries of $W_{ref}(s)$: $\eta_\cap(s)$ is defined between zero and p_{ref}. Graphically, $\eta_\cap(s)$ expresses the area in common between the two distributions (Fig. 4): higher $\eta_\cap(s)$, greater the similarity between the two distributions.

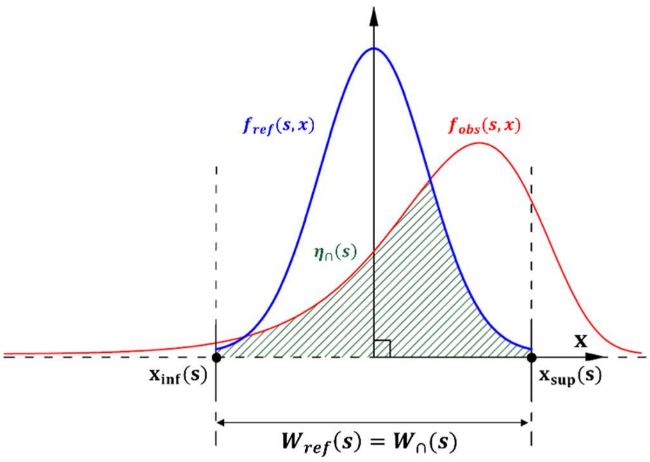

Fig. 4 Graphical representation of $\eta_\cap(s)$

In Fig. 5 different values of $\eta_\cap(s)$ are shown by comparing various Weibull distributions (scale parameter 'a' = 3, different shape parameters 'b') with the reference

Gaussian distribution ($\sigma_{ref}(s) = 1$ [cm]): the overlapping index is sensitive to the different distributions, and the highest value ($\eta_{\cap}(s) = 0.8619$) is obtained with the Weibull distribution (in magenta) closest to the Gaussian one. It is assumed that the reference tolerance $W_{ref}(s)$ has the width of 6 [cm].

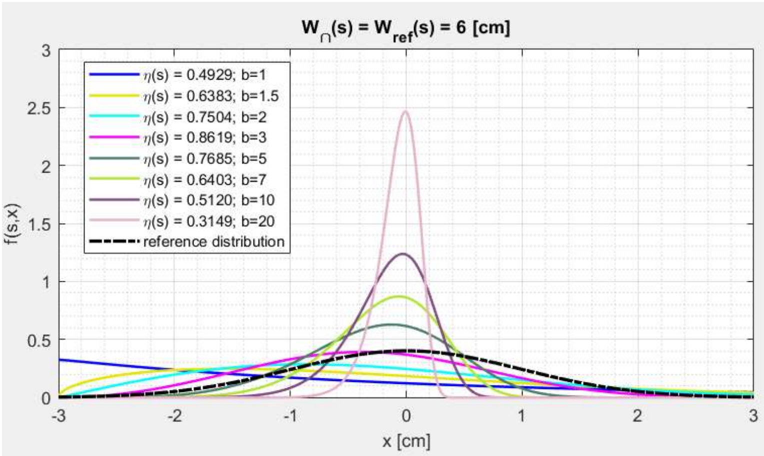

Fig. 5 Evaluation of $\eta_{\cap}(s)$ by comparing various Weibull distributions (scale parameter 3, b = shape parameter) with the reference Gaussian distribution; $q_{ref}(s)$ placed in 0.

At a curvilinear coordinate s, the behavior of the observed agent, with respect to the reference one, is entirely described by the three factors $W_{\cap}(s)$, $p_{\cap}(s)$ and $\eta_{\cap}(s)$. The only (hypothetical) case when the behavior of the observed agent can be described by one factor is when there is a perfect matching between the two agents: in this scenario $f_{ref}(s,x)$ and $f_{obs}(s,x)$ are identical, therefore $\eta_{\cap}(s) = p_{ref}$, bringing to $p_{ref} = p_{\cap}(s)$, and therefore to $W_{\cap}(s) = W_{ref}(s)$. In all the other cases, none of the three factors alone can describe the observed agent's behavior.

As an example, in Fig. 6 the two probability distribution functions $f_{ref}(s,x)$ (Gaussian distribution with $\sigma_{ref}(s) = 1$ [cm]) and $f_{obs}(s,x)$ (Weibull distribution with scale parameter 3 and shape parameter 7) are compared at a generic curvilinear coordinate s; the latter one is shifted along x to underline the different contributions of $W_{\cap}(s)$, $p_{\cap}(s)$ and $\eta_{\cap}(s)$, highlighting their mutual independence. In the first subplot each colored distribution is compared to the reference one (black dotted line), while values of the three factors (same color of the colored distribution) are shown in the last three subplots. In the figure, $\eta_{\cap}(s)$ is never equal to p_{ref} since the two distributions are different. Nevertheless, there are cases when $p_{\cap}(s) = p_{ref} = 99.73\%$ since the maximum value of $W_{\cap}(s)$ (4.15 [cm], last subplot) is lower than $W_{ref}(s)$ (6 [cm]): the region where spatial configurations are reachable by the observed agent is lower than the limits defined by the reference tolerance.

By focusing on the last two subplots in the range $x \in [-2; 0]$ [cm], while $W_{\cap}(s)$ is linearly increasing by approaching zero, $p_{\cap}(s)$ is almost constant: this effect is due to

the shape of the Weibull distribution, and in particular to the left tail of the distribution that causes $p_{\cap}(s)$ to be almost steady while shifting $f_{obs}(s,x)$ to the right.
In this range $p_{\cap}(s)$ is not as sensitive as $W_{\cap}(s)$, supporting more the mutual independence between the factors.

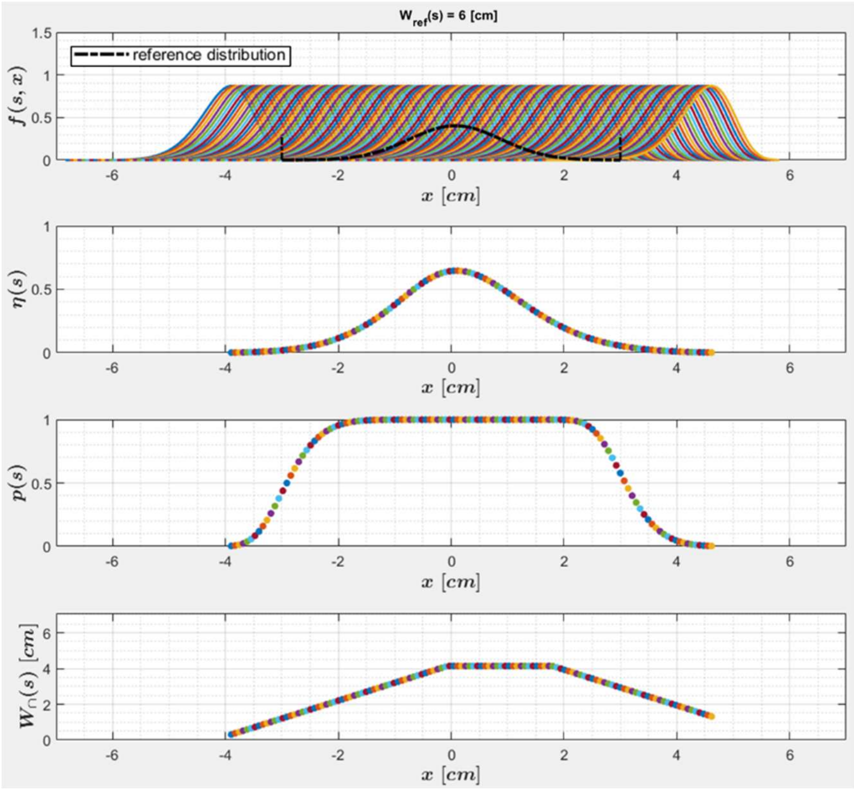

Fig. 6 Values of $W_{\cap}(s)$, $p_{\cap}(s)$ and $\eta_{\cap}(s)$ by comparing the reference Gaussian distribution with a Weibull distribution (scale parameter 3 and shape parameter 7) shifted along x. $q_{ref}(s)$ of the reference distribution is placed in 0.

2.3 Affordance Level

The overall behavior of the observed agent is evaluated through its motor difficulty ($ID_{\cap}$, equation 6), by considering $\widetilde{W}_{\cap}(s)$ (i.e., $W_{\cap}(s)$, $p_{\cap}(s)$, $\eta_{\cap}(s)$) along the average trajectory (t_{avg}) executed to accomplish the motor task. The overall behavior of the reference agent is evaluated through its motor difficulty (ID_{ref}, equation 4) by considering $W_{ref}(s)$ along the nominal trajectory (t_{ref}). The affordance level (α) is quantified by:

$$\alpha = \frac{ID_{ref}}{ID_{\cap}} = \frac{\int_{t_{ref}} \frac{ds}{W_{ref}(s)}}{\int_{t_{avg}} \frac{ds}{\widetilde{W}_{\cap}(s)}} \tag{10}$$

With $\widetilde{W}_{\cap}(s) = W_{\cap}(s) \cdot p_{\cap}(s) \cdot \eta_{\cap}(s)$. During the execution of a motor task, the observed agent tries to behave as the reference one: movements executed reflect the motor behavior, which is summarized by the Index of Difficulty. Greater the deviations from the reference agent, lower the values of the 'quantitative' ($p_{\cap}(s)$) and 'qualitative' ($\eta_{\cap}(s)$) factors as well as the 'extensive' factor $W_{\cap}(s)$. Since $p_{\cap}(s)$ and $\eta_{\cap}(s)$ are defined between zero and p_{ref}, and $W_{\cap}(s) \leq W_{ref}(s)$, the affordance level α is defined between zero and p_{ref}^2. The upper limit of α is p_{ref}^2 because when $\eta_{\cap}(s)$ is equal to p_{ref}, there is a perfect matching: therefore $p_{\cap}(s) = p_{ref}$ and $W_{\cap}(s) = W_{ref}(s)$. In this scenario, by considering $t_{avg} = t_{ref}$ and setting $\widetilde{W}_{\cap}(s) = p_{ref}^2 \cdot W_{ref}(s)$ in the denominator of equation 10, the affordance level is equal to p_{ref}^2. In the opposite case when $p_{\cap}(s)$, $\eta_{\cap}(s)$ and $W_{\cap}(s)$ tend to zero, α tends to zero. The preliminary analysis of the proposed quantitative metrics to evaluate the agent's affordance, show that α is defined in a continuous scale ([0; p_{ref}^2]) and can be applied in any research field involving agent's movements. The motor behavior of the observed agent is summarized by its motor difficulty $ID_{\cap}$, through the three independent factors ($p_{\cap}(s)$, $\eta_{\cap}(s)$ and $W_{\cap}(s)$) and the average trajectory t_{avg}. Various combinations of $p_{\cap}(s)$, $\eta_{\cap}(s)$ and $W_{\cap}(s)$ define different $ID_{\cap}$ values: by comparing $ID_{\cap}$ with the motor difficulty of the reference agent (ID_{ref}), the affordance level α is evaluated. Next section is devoted to show the effectiveness of the novel quantitative metrics through a numerical simulation.

3 Numerical Simulation

The affordance level is quantified through a numerical simulation by defining firstly the behaviour of the reference agent through $W_{ref}(s)$, t_{ref} and $f_{ref}(s,x)$. The shape of the nominal trajectory t_{ref} is shown in Figure 7. The extent of $W_{ref}(s)$ is set equal to 6 [cm], and it is assumed to be constant along t_{ref}. Spatial configurations (i.e., action possibilities) in the section orthogonal to t_{ref} at the curvilinear coordinate s are assumed to follow a Gaussian distribution, and $f_{ref}(s,x)$ is the corresponding probability density function (as in Fig. 2). $f_{ref}(s,x)$ is centred on t_{ref} with $\sigma_{ref}(s) = 1$ [cm] and $p_{ref}(s) = p_{ref} = 99.73\%$ for each s. The motor difficulty of the reference agent (ID_{ref}) is evaluated through equation 4. For sakes of simplicity, $f_{ref}(s,x)$ and $W_{ref}(s)$ are constant for each s, but in other scenarios, these features can change along t_{ref}.

The behaviour of the observed agent is expressed by the average trajectory (t_{avg}), while $\widetilde{W}_{\cap}(s)$ is quantified by $p_{\cap}(s)$ (equation 8), $\eta_{\cap}(s)$ (equation 9) and $W_{\cap}(s)$. The probability density function $f_{obs}(s,x)$ is defined a priori just for simulation purposes, while in other (observed) cases $f_{obs}(s,x)$ must be extracted from the spatial configurations $q_k(s)$ reached by the agent at the curvilinear coordinate s (as in Fig. 3). For the numerical simulation, the $f_{obs}(s,x)$ is considered as a Weibull distribution with scale parameter 3 and shape parameter 7, assumed to be the same for each s. To highlight differences between observed and reference agent, five t_{avg} are considered; as for $f_{obs}(s,x)$, the average trajectories are defined a priori for simulation purposes, instead of being evaluated from observed trajectories executed. From average trajectory 1 (t_{avg_1}), to 5 ($t_{av\ 5}$) deviations from t_{ref} increase, and therefore values of $\widetilde{W}_{\cap}(s)$ decreases. The motor difficulty of the observed agent ($ID_{\cap}$), for each of the five average trajectories, is evaluated through equation 6. Finally, the affordance level α is evaluated through the ratio $ID_{ref}/ID_{\cap}$ (equation 10). Results are depicted in the legend of Fig. 7.

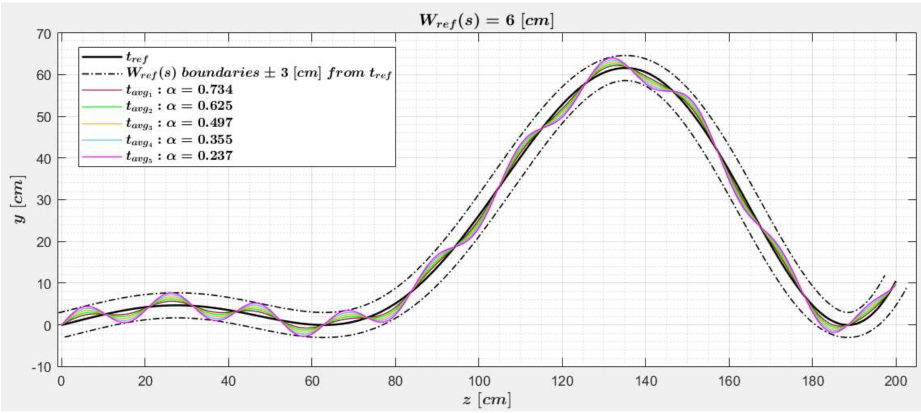

Fig. 7 t_{ref} and $W_{ref}(s)$ of the reference agent, the five average trajectories (t_{avg}) of the observed agent and the corresponding α values.

Results show the effectiveness of the proposed quantitative metrics in evaluating the agent's affordance through α. By increasing the differences of motor behaviours between the two agents, the affordance level α decreases from 0.734 ($t_{av\ 1}$) to 0.237 ($t_{av\ 5}$). Even in the best case considered (t_{avg_5}) α is not close to $p_{ref}^2 = 0.9946$, since it has not been considered the $f_{obs}(s,x)$ of a Gaussian distribution as for $f_{ref}(s,x)$. Even with the assumptions made for the numerical simulation, it is shown that α is able to capture the motor behaviour of both agents through the corresponding Index of Difficulty, and then quantify the affordance level by comparing the motor difficulty of the observed agent with the reference one.

4 Conclusions and Further Research

In this paper, a first sight on how to quantitatively evaluate the agent's affordance has been given through a mathematical formalism based on the Index of Difficulty. The agents' affordance can be a valuable tool to assess the performance of an agent during the execution of motor activities both in industrial and laboratory environments. In

industrial context, where there is the need to carry out motor activities (e.g. material handling, pick and place, manual assembly activities, navigation…), the motor performance depends on how the agent interacts with the environment during the execution of the task: this interaction is quantified through the agent's affordance by observing movements executed. The novel quantitative metrics is able to take into account movements executed by the observed agent and comparing them with the motor behavior of a reference agent. By considering this comparison through the motor difficulty of each agent, the affordance level is obtained.
Furthermore, in I4.0 industrial context, the quantitative metrics can be adopted also to optimize resource allocation problems by comparing the affordance level of different agents referring to the same motor activity, with the use of I4.0 technologies; the affordance level α can express the effectiveness of the human-robot collaboration, as well as the benefits in the adoption of new I4.0 technologies (e.g., haptic devices, augmented reality), during the execution of motor activities.
The proposed methodology can be considered as a starting point to unify and standardize the evaluation of affordance under a single quantitative metrics independent from the field of application (ergonomics, robotics, product design…), the specific motor activity (pick and place, manipulation, product assembly...) and the agent (robot, operator, co-bot).
Future steps will be focused firstly on testing the proposed quantitative metrics in real case studies. Once the affordance level is validated in case of experiments involving two dimensional-motor tasks, the model will be extended in case of three-dimensional motor tasks. A second goal will be focused on analyzing the agents' features that affect the affordance level, such as physical/control motor features, biomechanical properties, skills, experience, age, etc…, in order to understand which features need to be improved to increase the agent's ability.

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