To make robots that understand and adapt to human activity and vice-versa

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Abstract—This paper summarizes the motivation in mutual understanding of human activities and those of the robot. We then introduce successively control techniques for creating a repertoire of purely reactive sensorimotor functions (based on convex optimization techniques) and anticipatory from distributed predictive control methods. We then consider how to develop the robotic system the foresight to more or less long term to develop action plans and their implementation plan based on the principles of ideomotor integration.

I. INTRODUCTION

Tomorrow humans and robots will possibly share the same physical space, the same activities, help each other, etc. This perspective can and should conditioned the way in which we consider the design of robots. These robots we say collaborative must indeed be able to operate effectively and safely with humans. It is therefore necessary for them to understand human activities, the way in which they organize at the sensorimotor level but also at the cognitive level to better anticipate and generally interact with humans. Conversely, the robot must be predictable for humans. Therefore, it must have a deterministic behavior interpretable in a certain context based on a normative framework. To help in this, humans and robots need to share representations of movements, actions and objectives or methods of solving problems subtended by global functional objectives.

Beyond the development of the physically observable features, others not perceptible, are needed. Planning actions to achieve a goal, the selection of goals, the representation of actions and perceptions associated with the analysis of the context and affordances of objects, representations causing actions, etc. are key issues to make humans more understandable by robots and robots more cognitive.

The integration of a robot model of "psychomotricity" to enable it to have the means to predict or at least explain a posteriori the human physical behavior and its effects, to understand this in an appropriate form its interaction with humans [1].

The communication between the robot and the human can obviously benefit from body language (posture, gestures, etc.). Indeed, in humans 75% to 95% of communication is non-verbal [3]. This form of communication can provide access to a deeper reading of emotions (boredom, interest, sadness, etc.) even intentions of the person. Body language thus creates a very important part of the interaction with a person: The body then gives a certain "form" in mind.

Beyond signs, be able to understand and anticipate human activity directed towards a goal is an important element to optimize, through interaction, the activity of the robot perception and motor activity. To reach this understanding, we can try to rely on how the brain generates predictions. A hypothesis on the predictive coding suggests that the brain continuously generates expectations on sensory input from motor activities. This hypothesis derives from the ideomotor theory [2]. It considers that actions are cognitively represented in terms of their perceived effects. This principle of ideomotor argues that during the execution of a particular action, a motor model (a reduced order model) is automatically associated with the input of perception representing the perceptual effects of the action [3]. Perception and action planning are considered similar processes based on the characteristics of activation codes that represent external events.

Having such a model must at least allow to design the robot functions (communication, perception, action) in a form directed by the interaction as we do for any other man-machine interface. Using a biologically inspired model of cognition for the planning and control of robot motor activities may conversely facilitate the understanding of its behavior by users.

This paper summarizes the motivation comes in the understanding of human activities and those of the robot. We then introduce successively control techniques for creating a repertoire of purely reactive sensorimotor functions based on convex and anticipatory from methods of predictive control and distributed optimization techniques. We then consider how to develop the robotic system the foresight to more or less long term to develop action plans and their implementation plan based on the principles of ideomotor integration. We will consider an implementation of coding in this ideation process, this "predictive machine", interactions between perceptions and actions.

The integration of the two "sensorimotor" and "ideomotor" levels in the management of motor activities thus defined can have a formal framework for the development of the robot's behavior with respect to an objective and for the interpretation of human behavior.

II. LQP-BASED WHOLE BODY CONTROL

Building a repertoire of automatic and adaptive sensorimotor functions and the generation of trajectories may result from the optimization of functions from the task observation of effects (optimal control) as claimed by cognitive approaches or methods of adapting dynamic patterns coordination constraints and task environment. For this plasticity is used offline optimal control or learning such
mechanisms. We can thus make a "machine to respond" that automatically respond to the demands of its environment through coordinated mobilization adaptable to environmental constraints sensorimotor functions. This directory of more or less developed can be expanded over time to acquire new skills by learning. This learning mobilizes cognitive level analysis models usually used by neurophysiologists to study sensorimotor mechanisms.

Motor actions are prepared in the form of an assembly of elementary functions (basic patterns engines) and structured by a higher-order scheme. The motor command encodes not only the dynamic properties of the motor and the tasks carried out in the form of goals that are related to properties of objects on which the action applies system: the shape and size of the object, the presumed weight of the object, etc. Jeannerod refers to this mode of representation by the operator of its environment, as a pragmatic representation, representation centered on the object-oriented way and to act on them .7

The attributes of objects are treated in this pragmatic representation as affordances, enabling certain primitive motor control. They are directly used to define the parameters of the elementary motor actions guiding the kinetic performance: speed, strength, amplitude, direction, placement of certain body parts.

The synthesis of motor activity for a robot, guided by the tasks defined from the attributes of objects and conditioned by constraints inherent to the system and those of the environment can be achieved in a generic form based on different techniques to control complex systems the formalism of linear quadratic programming.

Robotics literature offers two main classes of hierarchical architectures for the control of humanoid robots, differing by the algorithm of high-level coordination. The first approach is a strict hierarchy based on a projection waterfall in the core operations of highest priority [4]. The second [5] adopts a strategy of coordination relative weight that defines through cost optimization consensus among conflicting objectives within an overall goal.

These methods have applications to control humanoid robots for the simultaneous execution of several dynamic tasks for example in the work of Sentis respectively [6] and Salini et al. [7].

From the perspective of a real integration, the command generated must have a certain continuity, a point may be critical during transitions between changing priorities. In the case of projection strict continuity of these transitions can be obtained [8] by rewriting the control laws of each elementary operation as a differential equation that defines the expected decrease of the error with respect to the objective at a given initial state. Part of the hierarchy by weighting ensures the continuity of the control more intuitive for example by imposing a continuous evolution of the weights during transitions priority [9]. A second critical issue in humanoid robot control is the constraints. These constraints can for example limit the capacity of actuators and restrict efforts to contact a domain (non-slippage, for example). If equality constraints can be taken into account so in the case of algebraic prioritization projection as in [10] to ensure non-movement of the contact points on the ground, the inequality constraints are can in this context being approached by projection a posteriori solutions or task definition to remove the edges of acceptable solutions area by potential field methods such as [11]. The optimization problem stated by the methods by weighting allows, through numerical methods, to produce solutions within a constrained area. The inequality constraints can indeed be expressed directly in an optimization problem under constraints, such as is the case for contact with friction [12] or more scope for any linear constraint [7], for example limitations of the actuators.

1) Prioritization by relative weighting: This method considers a set of objectives minimization under constraints aggregated into a single cost function. The solution is then generated a consensus among basic goals set by their relative weighting.

We recall the equations of motion of polyarticulated systems, obtained [13] by the Lagrange formalism and are then of the form

\[ M(q) \ddot{q} + n(q, \dot{q}) + g(q) = \tau + \gamma_c, \] (1)

The formalism described in [7] defines objectives as torques kinematic \( \tau^j \) or stress \( \sigma^j \) desired, expressed at a point of the robot (operational) or into the joint space. The function associated task \( T_j \) is defined by

\[ T_j(q, \dot{q}, \tau, F^c) = ||E_j(q) \left[ \begin{array}{c} \tau \\ F^c \end{array} \right] - f_j(q, \dot{q})||, \]

where the matrix \( E_j \) and \( f_j \) the vector are defined to express \( \tau \) as the error between the kinematic torsor \( t_j \) (resp. of stress \( w_j \)) Effective product by \( (\tau, F^c) \) in the state \((q, \dot{q})\) and the kinematic screw \( \tau^j \) (resp. stress \( \sigma^j \)) desired. \( F^c \) represents the operational actions torsor contacts whose Jacobian \( J^c \) is such that, by taking the notation view 1, \( \gamma_c = J^c F^c \).

The problem of multi-objective control is then constrained to find the couple \((\tau, F^c)\) minimizing a set of \( n_t \) tasks \( T_j \). This set is gathered centrally in one objective function defined as the weighted sum of \( n_t \) basic objectives \( t_j \). The control problem can then be written to a state \((q, \dot{q})\) system

\[
\min_{\tau, F^c} \sum_{j=1}^{n_t} \omega_j T^2_j(q, \dot{q}, \tau, F^c),
\]

\[ \text{t.q.} \left\{ \begin{array}{l}
G \left[ \begin{array}{c} \tau \\ F^c \end{array} \right] \preceq h \text{ et } C \left[ \begin{array}{c} \tau \\ F^c \end{array} \right] = b
\end{array} \right\},
\]

where \( \omega_j \) weight the relative influence of goals \( t_j \) and couples matrix-vector \((G, h)\) and \((C, b)\) respectively express the inequality constraints and equality defining the permissible range of variables \((\tau, F^c)\).

This formalism allows to take into account inter alia the technological limitations of the system (torque, position, speed and acceleration bounded joint) and the non-moving contact points. An approximation of friction cones can also guarantee their non-slip model in a dry Coulomb friction.
However, in the case of conflicting objectives, the resolution form of consensus does not guarantee the achievement of the overarching objectives, unlike projection methods. Hybrid methods as described in [14] define each priority level similar optimization problems and then solved recursively.

The following sections describe reactive and predictive approaches to determine, through a strategy of minimizing an error for a particular purpose, kinematic torques $t_f^j$ or desired force $w_f^j$.

III. MODEL PREDICTIVE CONTROL

This section introduces predictive control approaches under the Model Predictive Control (MPC) formalism, which can be denoted in the literature by Dynamical Matrix Control (DMC), Generalized Predictive Control (GPC) and Receding Horizon Control (RHC). The predictive aspect of such control formulations comes from the consequences preview of the control solution on the system state, over a future horizon. An analogy can be made between such a control approach and the anticipative mechanism humans operate to react rapidly to incoming events: the illustration in figure 1 displays how a driver can employ a learnt model of his car to anticipate a safe trajectory to avoid collision while maintaining the control of his vehicle and staying on the road. On the contrary a purely reactive mechanism might lead to a strong deviation of the vehicle without considering off-course risks or obstacle movements.

![Fig. 1. Illustration of the predictive approach](image)

MPC methods rely on a similar principle: at each control step an optimal future horizon of control inputs is computed with respect to a dynamical model of the controlled process, the current system state and an objective function capturing, in general, the error to a reference trajectory of variables of interest; the first element of this horizon only is input to the system, as the computation is actualized at the next control step.

A. Introduction

With the objective to compute at each control step a solution minimizing a specified error over a receding future horizon, these methods typically use numerical constrained-optimization algorithms. Control problems are generally formulated in a LP (Linear Program) or QP (Quadratic Program) form.

A first apparition of a MPC problem [15] can be found in a LP form in the works of Propoi [16] dealing with optimal control problems. A decade later the Model Predictive Control designation appears (MPHC, Model Predictive Heuristic Control) in the works of Richalet et al. about industrial process control [17], minimizing a quadratic objective function with a constrained, iterative heuristic algorithm relying on an identified model of the controlled process (IDCOM, Identification and Command). The works of Culer and Ramaker later propose to write the control problem as a Least-Squares minimization [18] (DMC), and in 1983 a QP problem is defined with Morshedi [19] to explicitly account or constraints in the optimization problem (QDMC).

Despite designation and formulation differences, these methods rely on shared fundamental principles: the control problem is solved through the optimization of the future evolution of controlled variables, previewed with respect to a model of the controlled system.

The illustration in figure 2 presents in such terms the concept of predictive control. A generic formulation of the MPC problem is introduced in the following sub-section.

![Fig. 2. Concept of predictive control](image)

B. Model Predictive Control problem

The invariant system described in discrete time by the following process is considered

$$\forall k \in \mathbb{N}^*, \forall u_k \in \mathcal{U}_u^k, \begin{cases} x_{k+1} & = f(x_k, u_k), \\ y_k & = g(x_k) \end{cases}$$

(2)

where $u$, $x$ and $y$ respectively denote the control (input), state and output variables of the system and are displayed in figure 3.

![Fig. 3. Simple MPC architecture](image)

In the case of a linear process, the description (2) can be written

$$\forall k \in \mathbb{N}^*, \forall u_k \in \mathcal{U}_u^k, \begin{cases} x_{k+1} & = A x_k + B u_k, \\ y_k & = C x_k \end{cases}$$

(3)

where matrices $A$, $B$ and $C$ implicitly describe the linearity of the system with respect to input variables, i.e. $u$. The sets $\mathcal{X}_u^k \subset \mathbb{R}^m$ and $\mathcal{X}_y^k \subset \mathbb{R}^n$ are delimited by the constraints on inputs and outputs of the system, for example from
technological limitations or the the environment.
Without any loss of generality, prediction and control hori-
zon (cf. figure 2) are considered as identical in this docu-
ment. With $\mathcal{U}_{N/k} \triangleq \{ u_{k|k}, \ldots, u_{k+N-1|k} \}$ an horizon of input
variables $u$, the objective function $g_k$ at step $k$ is defined as
$g_k(x_k, \mathcal{U}_{N/k})$ over an horizon of $N \in \mathbb{N}^+$ time steps for the
measured system state $x_k$.
A widespread form of objective function $g_k$ in the case of
linear processes (3) is quadratic1 with respect to each of the
input $u$ and output $y$ variables of the system, optimized with
constraints on the input variables $u$ only.
In a generic manner, with $\mathcal{U}_{N/k} \triangleq \{ y_{k+1|k}, \ldots, y_{k+N|k} \}$ an
horizon of outputs of the linear process (3), a quadratic cost
function $g_k$ can be written as
$$g_k(x_k, \mathcal{U}_{N/k}) = \mathcal{W}_{N/k}^T \mathbf{P} \mathcal{W}_{N/k} + \mathcal{W}_{N/k}^T \mathbf{R} \mathcal{W}_{N/k}$$
where $\mathbf{P}$ and $\mathbf{R}$ are symmetric positive definite matrices
defining, for example, weighted euclidean norms of the sys-
tem inputs and outputs. A common form aims at minimizing
the outputs $y$ norm and the variations of inputs $u$, which
brings
$$\begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix} \quad \text{et} \quad \begin{bmatrix} 0 & \cdots & 0 \\ 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix}$$
with
$$\mathbf{D} \triangleq \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & 1 \end{bmatrix}$$
where $\omega_b$ and $\omega_u$ are scalar coefficients weighting the relative
influence of each term in the optimization problem.
According to the discrete description (3) of the linear system,
the recurrence over the horizon $\mathcal{N}$ can be written
$$\mathcal{W}_{N/k} = \mathbf{G} x_k + \mathbf{H} \mathcal{W}_{N/k},$$
where
$$\begin{bmatrix} \mathbf{C} A \\ \vdots \\ \mathbf{C} A^N \end{bmatrix} \quad \text{et} \quad \begin{bmatrix} \mathbf{C} B & \cdots & 0 \\ \vdots & \ddots & \vdots \\ \mathbf{C} A^{N-1} B & \cdots & \mathbf{C} B \end{bmatrix}$$

The minimization objective (4) is written, with (5), explicit-
ly as a function of the optimization variable $\mathcal{W}_{N/k}$and of the
actual system state $x_k$
$$g_k(x_k, \mathcal{W}_{N/k}) = \mathcal{W}_{N/k}^T (\mathbf{H}^T \mathbf{P} \mathbf{H} + \mathbf{R}) \mathcal{W}_{N/k} + 2 (\mathbf{H}^T \mathbf{P} x_k)^T \mathcal{W}_{N/k} + \mathbf{x}_k^T \mathbf{G}^T \mathbf{P} \mathbf{x}_k$$

The predictive control problem consists in finding, for the
actual state $x_k$ of the system, an optimal horizon $\mathcal{W}^*_{N/k}$ of
admissible inputs with respect to $g_k$ and the constraints on
the system. It writes
$$g_{k+1} = \min \mathcal{W}_{N/k} \frac{g_k(x_k, \mathcal{W}_{N/k})}{t.q. \; \forall i \in \{0, \ldots, N-1 \}}$$

With $\mathcal{W}^*_{N/k} \triangleq \{ u^*_{k|k}, \ldots, u^*_{k+N-1|k} \}$ the optimal horizon
of input variables with respect to $g_k$, $u^*_{k|k}$ only is applied
to the system and the problem is solved at the following
control step $k+1$ with $g_{k+1}$.

Without constraints on the input and output variables,
$i.e.$ $\forall k \in \mathbb{N}^*, \mathcal{X} _{u} = \mathbb{R}^n$ and $\mathcal{X} _{y} = \mathbb{R}^m$, a simple form of $g_k$ can
allow for an analytical resolution of the MPC problem (7).
However, one of the major advantages of predictive tech-
iques is their ability to explicitly account for a set of
constraints on the system; in a large variety of applications
the MPC problem is hence solved with numerical methods.
For example in the case of a quadratic objective function,
constraints on the solutions $u$ are frequently bounds to
respect in order to account for the system limitations; the
constraint $\{ u \in \mathcal{X} _{u} \}$ is hence commonly written as a set of
linear inequalities, i.e. $\mathcal{X} _{u}$ is a polyhedron3. The predictive
control problem (7) is then, subject to convexity conditions,
a Quadratic Program (QP).

IV. DISTRIBUTED MODEL PREDICTIVE CONTROL

Distributed control is an alternative to centralized and
decentralized control architectures. Applications of MPC to
industrial processes of large dimension rapidly met the limits
of centralized approaches, and the lack of stability guarantees
for decentralized methods might in certain cases overtake
the advantages brought by the dimensionality reduction they
provide. Distributed approaches consist in the decomposi-
tion of the system in autonomous sub-systems, organized within
an information exchange network. The sparse aspect of the
majority of large systems is exploited in order to bypass
the drawbacks of centralized architectures: sub-systems com-
monly interact with their respective neighbors solely.

The setting up of a distributed control architecture requires
to apprehend the coordination problem of local controllers.
Model Predictive Control is a suitable framework in this con-
text as it offers a time within which a coordination strategy
can be settled. Distributed Model Predictive Control (DMPC)
is hence the application of MPC methods to distributed
architectures.

Two classes of distributed architectures can be distin-
guished depending on the range of the cost function they
involve: a cooperative architecture considers a global ob-
jective and non-cooperative architectures coordinate sub-
systems with local objectives. For each of these classes
information exchange can be unilateral or bilateral (figure 4).

1 The formulation of a task function as the euclidean norm of an error
between a linear variable of interest and a reference can lead to the definition
of a quadratic program

2 or in the case of equality constraints only

3 for stability reasons the polyhedron $\mathcal{X} _{u}$ must contain the origin
In the case of unilateral communication between controllers, their evaluation can be sequential; the sequential approach is opposed to parallel methods where controllers exchange information in a bilateral way.

The performances of distributed methods mainly rely on the coordination of coupled sub-agents. Specific attention must hence be drawn to the structure of the information exchange between controllers.

V. RESULTS

A distributed control architecture, coordinating an horizon of inputs for two reduced representations of manipulation and balance tasks, is proposed as a suitable framework to solve the problem of task-posture adaptation. The dynamics of the upper-limbs is previewed under the influence of an external action applied to the effector, allowing for the evaluation of an horizon of disturbances on the lower-limbs dynamics. The dynamics of both sub-systems is then optimized over a future horizon with respect to postural stability and manipulation performance criteria.

These simultaneous tasks are fundamentally conflicting: although a strong stiffness of the manipulation task leads to a better tracking, it induces a greater disturbance on the center of mass which threatens postural balance. The controlled behavior of the effector is adapted in an anticipative manner jointly with the center of mass trajectory in order to compromise between manipulation performance and balance keeping. The validity of this distributed predictive approach is assessed through the simulation of a humanoid robot performing two concurrent tracking tasks, as illustrate in figure 5: it maintains biped balance while following a predefined path with its right hand where is applied a known external effort in lateral and longitudinal directions.

Simulated experiments are performed using Arboris-Algorithm-Python [?], an open-source dynamic simulator developed at ISIR with the Python programming language, involving a rather accurate model of the iCub robot [?] with 38 degrees of freedom and 4 contact points at each foot. Four controllers are compared:

1) $C_1$: ZMP Preview Control[20],
2) $C_2$: ZMP Preview Control accounting for external force at the hand as directly applied on the CoM,
3) $C_3$: Distributed control $\omega_m/\omega_p = 10$,
4) $C_4$: Distributed control $\omega_m/\omega_p = 0.1$.

Coefficients $\omega_m$ and $\omega_p$ respectively weight the influence of the manipulation and balance errors within the global objective function minimized by the distributed control approach. Controller $C_3$ prioritizes the manipulation tracking performance over the ZMP task, and $C_4$ is parameterized symmetrically. Cumulated normalized tracking errors for both tasks and the four controllers are presented on figure 6.

These results show the noticeable gain in balance provided by the introduction of an approximation (considered to be applied on the CoM) of the external effort. Second, the preponderance of the manipulation task in the controller $C_3$ leads to a significant increase in the tracking performance of the hand though causing a slight prejudice to balance, while symmetric parameters lead to weaker gains but for both tracking tasks.

An intuitive trend in the stiffness strategy is computed online by controllers $C_3$ and $C_4$: controller $C_3$ tends to opt for a manipulation stiffness higher than the pre-defined reference, whereas $C_4$ tends to loosen the manipulation task stiffness in favor of balance, notably at critical steps where the external action on the hand is close to its maximum amplitude.

The performance gain in balance tracking provided by the consideration of the external action is notable. However, balance failure-prone short-term effects at critical steps require a better estimation and adaptation of the transmission of the external action on the CoM that controllers $C_3$ and $C_4$ provide.

The distributed predictive formulation produces a robust and parameterizable control architecture identifying in an anticipative manner an optimal control strategy in favor of antagonist objectives.
VI. CONCLUSION

Sensorimotor functions show some responsiveness to the demands of the environment, including for voluntary activities. They base this on an integrative level which manages and organizes motor activities on the basis of certain representations of the outside world. It is the articulation of the ideomotor on these representations level with sensorimotor functions that the system acquires the capacity to act and not just react. This is predictively, by projection and extrapolation on different horizons the effects of actions, the system is able to develop action plans and plan execution. This cognitive level operates on figural or symbolic representations of the physical effects of the system with respect to the goal. It has been shown that the intention to act develops several hundred milliseconds before the action is triggered. Integration at sensorimotor and ideomotor levels of the management of motor activities is a particularly complex issue. It is based on a multiplicity of sensorimotor dialogues included in the structures of the machine on which act organized cognitive management of the action. A paradigm for achieving dynamic selection of primitive non-deterministic action on the basis of fuzzy rules for the implementation of activities defined as goals of the objects is proposed in [9].

REFERENCES