Self-Awareness in Autonomous Systems

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Introduction

- What is Self-Awareness?
- Some definitions first
- Self-Awareness is:
  - “A conscious knowledge of one's own character and feelings”
  - “An awareness of one's own personality or individuality”
- A physical process from a Neurology standpoint
  - We’re not sure how exactly self-awareness arises in Ego-things
- A mental process from a Psychology standpoint

What is Self-Awareness?

- Nassier argues about 5 levels of self-knowledge:
  - ➢ The ecological self
  - ➢ The interpersonal self
  - ➢ The extended self
  - ➢ The private self
  - ➢ The conceptual self
- These layers are developed in parallel from infancy
- Self-awareness arises by the interaction of the various levels of self-knowledge

What is Self-Awareness?

- Many things around the subject are still unclear
- Its foundations are not proven to exist
  - Some Neurologists argue it’s an illusion
- There is no genuine theory of the underlying principles and methods that give rise to true Self-Awareness
- This makes implementation ever so harder
- Some propose to ground it in the solid theoretical framework of Integrated Information Theory

Technical Difficulties

- Extremely demanding processing capabalities in order to run live
- High complexity of inter-connected algorithms and systems
- Training requires huge amounts of properly refined data
- Real-world implications which require:
  - ➢ Extreme reliability
  - ➢ Accuracy
  - ➢ Conflict-resolving ability

Motivations for Self-Awareness in robots

- The benefits are endless
- The path to AGI / Superintelligence goes through machines that are Self-Aware
- Conscious, meta-selfaware Ego-things
  - Can assist humans in every aspect of their lives
- Huge advancements for
  - Medicine
  - Industry / IT sector
  - Biology, Physics, Computer Science, Engineering, etc.

Motivations for Self-Awareness in robots

- Introducing self-awareness to computing systems will increase their usability by making them more:
  - Efficient
  - Resilient
  - Flexible
  - Adaptive
  - Responsive to dynamic environments
- Self-Aware assisting systems will be the ultimate tool for humanity's further development

Past Work

Some existing cognitive architectures:

- ACT – R (2004) (Adaptive Control of Thought-Rational)
  - ➢ Classical rule-based system
  - ➢ (facts + events) organized with (production rules + procedures)
  - ➢ Memory contains “chunks” of data
  - ➢ Rules applied to chunks lead to:
    - o Robot action in the world
    - o Change in declarative memory
  - Chunks that are frequently selected have a higher chance of being selected again

Cognitive Architectures

- ACT – R (2004) (Adaptive Control of Thought-Rational)
  - ➢ New rules are created from trying to achieve goals
  - ➢ Costs and Success rates of the rules converge through an optimization procedure
- SOAR (2006) (State, Operator And Result)
  - ➢ Aims to model human cognition
  - ➢ Knowledge represented by production rules
  - ➢ Rules conditions are matched to working memory, where attributes and values are encoded
  - ➢ “Chunking” + reinforcement learning produce new rules

Cognitive Architectures

- SOAR (2006) (State, Operator And Result)
  - Reinforcement learning rewards “good” behavior, resulting in a chain of rules
  - The new rules abstract the succession of rules to achieve the desired goal
- SISSY (2013) (Self-improving System Integration)
  - Intelligent integration of complex systems
  - Systems have sub-systems that can be:
    - Adaptive
    - Non-Adaptive

Cognitive Architectures

- These existing architectures have a lot in common:
  - ➢ Symbolic representations
  - ➢ Production rules
  - ➢ High levels of abstraction
- But they have some significant negatives:
  - ➢ They don’t address the issue of operating in real time
  - ➢ Can’t build novel internal representations from sensory data (ACT-R, SOAR)

Existing Work

- There are constantly new models appearing to tackle these issues
- Many approches proposed for implementing Self-Awareness to Autonomous Systems.
  - Some are purely theoretical
  - Most involve physical + abstract models
- We will discuss these approches from now on

A theoretical approach

- “Levels of Networked Self-Awareness” (2018) L.Esterle, J. Brown
- Tackles the issue of live runtime of SISSY systems
- Self-Awareness alone is not enough
- Self-Aware systems must be aware of the self-awareness of other systems.
  - ➢ Just like humans, e.g. a baby falls into inanimate objects until it learns these objects are not self-aware
- These systems create networks

Levels of Networked Self-Awareness

- They define 5 levels of networked self-awareness:
  1) Networked Stimulus-awareness
     - The system doesn’t know if the stimuli is internal or external
  2) Networked Interaction-awareness
     - Models the effects of interactions of others on itself
  3) Networked Time-awareness
     - Keeps information about past stimuli, and potentially predicts future
  4) Networked Goal-awareness
     - Understanding others’ and own goals and potentially changing them
  5) Networked Meta-self-awareness
     - Ability to determine its own level of networked self-awareness

Levels of Networked Self-Awareness

- This approach is promising the future of self-integrating systems
- Each individual will understand the goals of others
- Potentially systems that will function without the assist of humans in live runtime

Another approach

- "Towards Self-Aware Robots" (2018), by Chatila R, Renaudo E, Andries M, Chavez-Garcia R-O, Luce-Vayrac P, Gottstein R, Alami R, Clodic A, Devin S, Girard B and Khamassi M
  - A more sophisticated and hands-on approach
- Self-awareness must first rely on perception of self as different from the environment and from other agents
- This is achieved via "Perception and Affordance learning"
- The robot develops sensorimotor representations and not just exteroceptive representations
  - Perception is thus not an isolated process
  - The robot learns that the same object can have different meaning to different individuals
  - A link between self-awareness and situation-awareness is formed

Perception and Affordance learning

- The robot has processes that integrate four inputs:
  - Perceptual
  - Proprioceptive
  - Contextual
  - Its own action capabilities
- Structural learning of a Bayesian Network representing this data
  - The robot discovers correlations between itself and the environment
- Inferred info can be used for
  - learning decisions
  - future planning tasks, or
  - adding sensor and motor capabilities to the innate repertoire.

Perception and Affordance learning

- Environment is over-segmented by VCCS (Voxel Cloud Connectivity Segmentation) into supervoxels
- Supervoxels
  - Evenly distributed
  - 39-D feature vector
    - 3 color coordinates (R,G,B)
    - 3 spatial coordinates (x,y,z)
    - 33 elements from an extension of the Fast Point Feature Histogram
  - Clustering process groups the supervoxels that possibly correspond to the same object

Perception and Affordance learning

Source:https://www.frontiersin.org/articles/10.3389/frobt.2018.00088/full

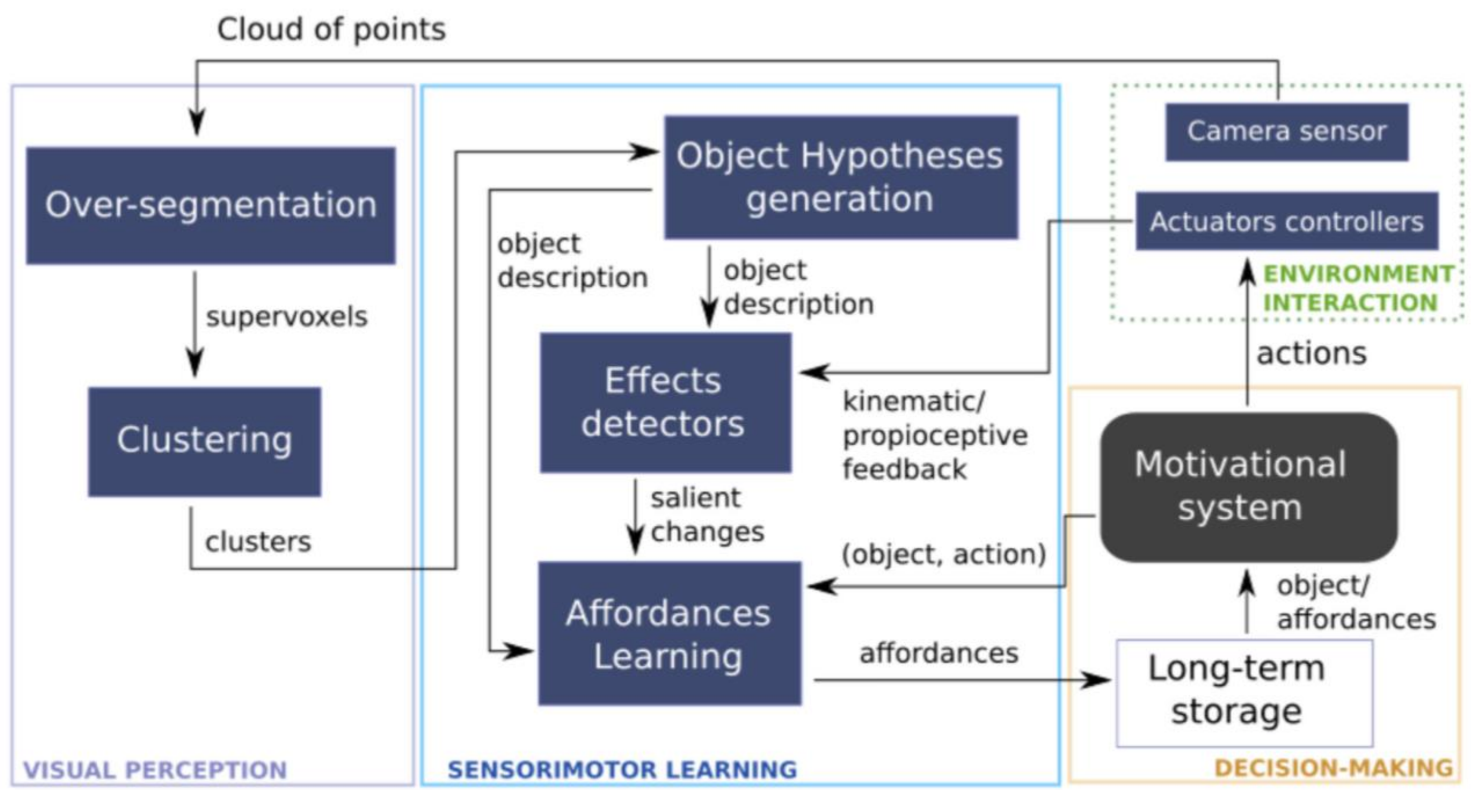

FIGURE 1 | Architecture of the proposed sensorimotor approach for scene affordance learning.

Perception and Affordance learning

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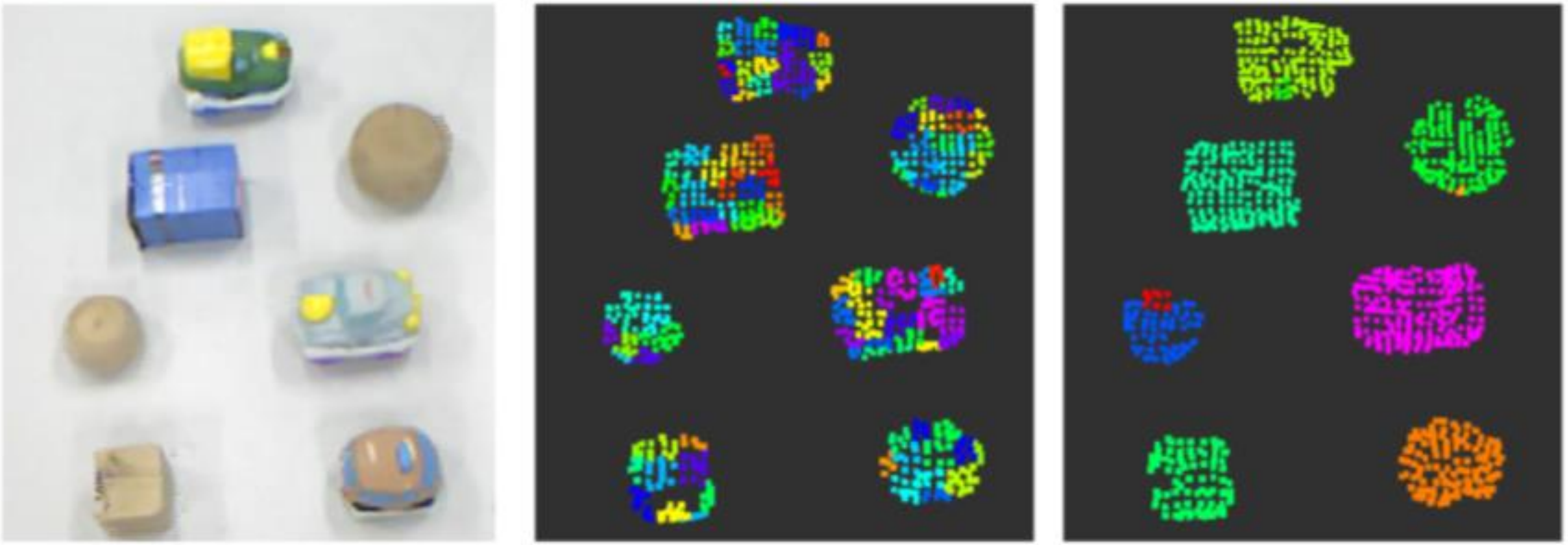

FIGURE 2 | Results from the perception process. Appearance and spatial information from the RGB-D point cloud of the real scene **(Left)**; supervoxels from over-segmentation of the point cloud **(Middle)**; and results from intrinsic clustering **(Right)**.

Perception and Affordance learning

- The robot also learns by manipulating objects
- Define as O the set of objects, A the set of actions, and E the set of observable effects
- An affordance α is defined as:

$$\alpha = \big((ok, al), ej\big), for\ ok \in O, al \in A\ and\ ej \in E,$$

- Example of the “grasp-ability” effect:

Perception and Affordance learning

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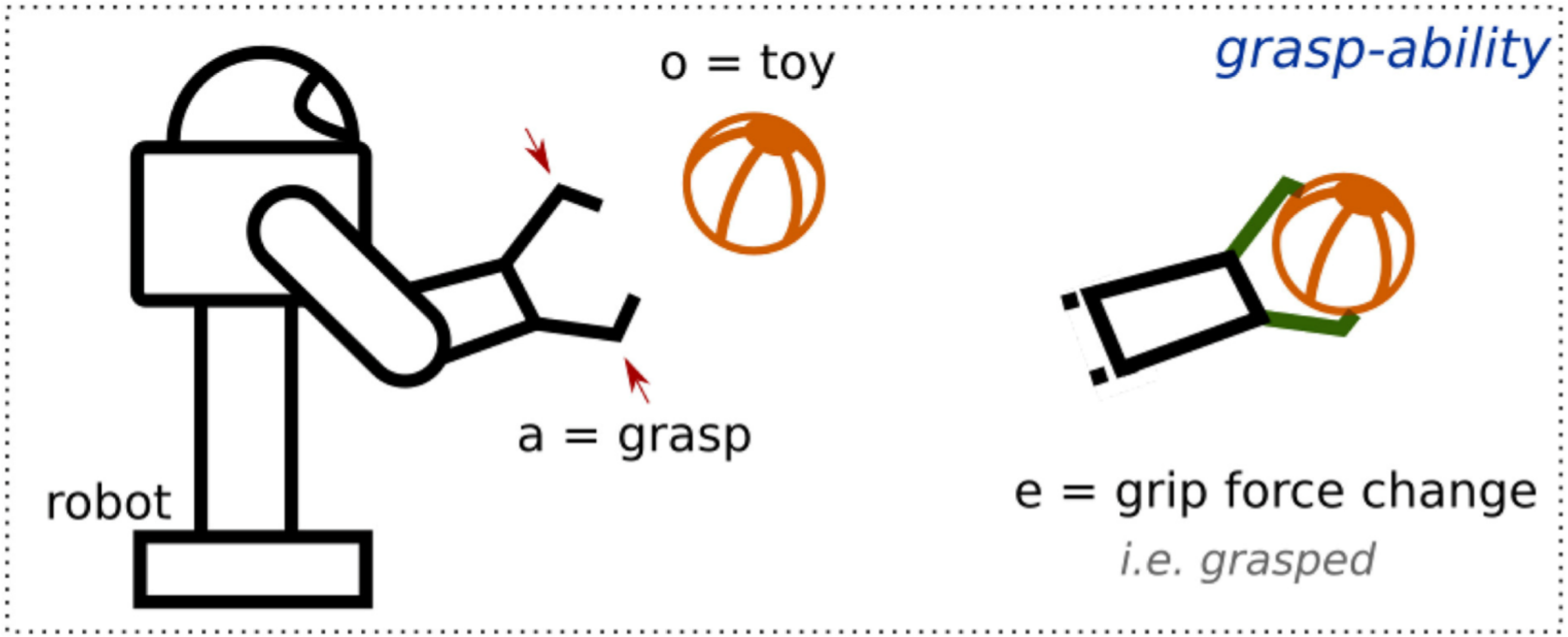

FIGURE 3 | Representation of the *grasp-ability* affordance relation.

Perception and Affordance learning

- Create a Bayesian Network B from O, A, E
  - ➢ Consider each element from these sets as a random variable
  - ➢ Find dependencies in B, $P(B|D)$, where D is the interaction data
  - ➢ Affordances are described by these conditional dependencies
- Create many such structures
  - ➢ Define score for each one based on # of bits required for encoding
  - ➢ Pick one after applying a Hill Climbing search algorithm
- Moving on to the decision-making strategies

Learning Actions and Plans

- Implement two different strategies for decision-making
  - Enables more Autonomy and Adaptation
  - The robot can analyse the efficiency of its decision-making process
  - It can use this to change the way it generates its behavior
- A meta-controller within the robot chooses between the two
- Goal-directed strategy
  - Has a whole picture of the environment
  - Model based method
  - Develop using reinforcement learning
    - Rewards based on transitions between environment states

Learning Actions and Plans

- "Habitual behavior" strategy
  - Model-free method
  - locally learns the reward-predictive value associated with each state-action pair without explicitly taking into account the effects of the action predicted by a world model of the task.
- a_{hab}: Habitual behavior action
- a_{GD}: Goal-directed action

Learning Actions and Plans

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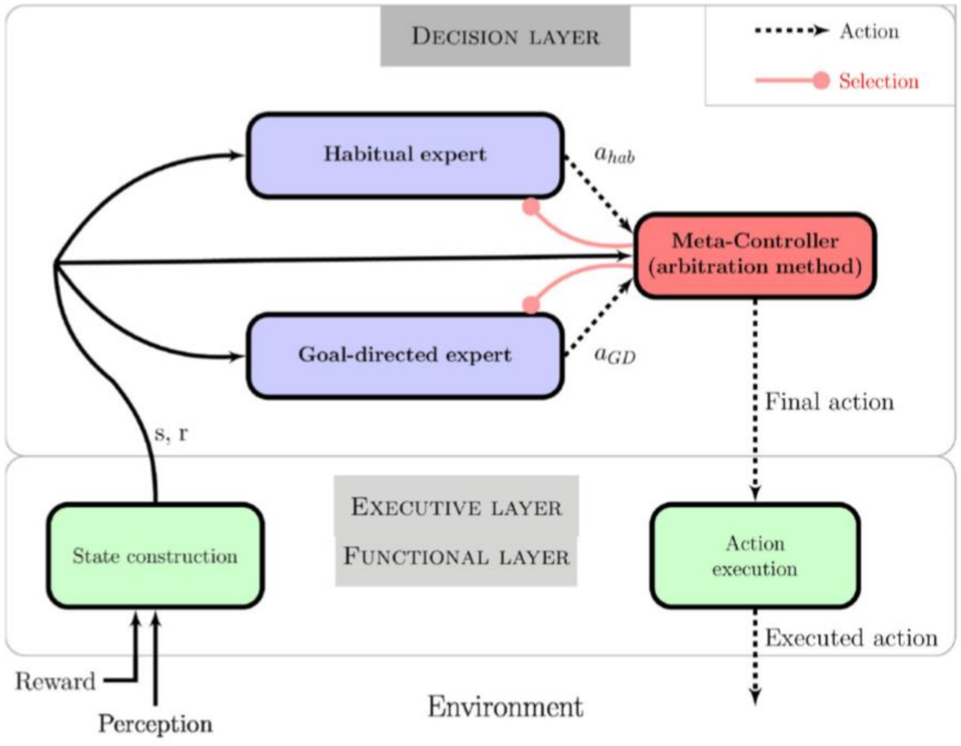

FIGURE 4 | Global action selection architecture composed of two decision systems implementing corresponding behaviors: the goal-directed expert is a model-based RL algorithm whereas the habitual expert is a model-free RL algorithm. The meta-controller is in charge of monitoring different expert information, giving control to one of the two. The reward information comes from the motivational system and represents the goal of the task.

Learning Actions and Plans

- The meta-controller uses coordination methods to:
  - Analyze each strategy
  - Select which one will control the robot for any action
- This has many beneficial effects:
  - Tasks are fulfilled more efficiently
  - The robot can criticize and report on its own actions

Joint Human-robot action

- The robot’s cognitive ability can be additionally enhanced
- Joint actions between humans require levels of self-awareness
  - E.g. dancing with a partner
- Human-robot joint actions add a second level of awareness
- Proposed framework that permits the robot to:
  - Estimate the mental state of its human partner
  - Mental state that consists of
    - State of the world, goals, actions and plans

Joint Human-robot action

- A PR2 robot sharing with a human the goal of cleaning a table:

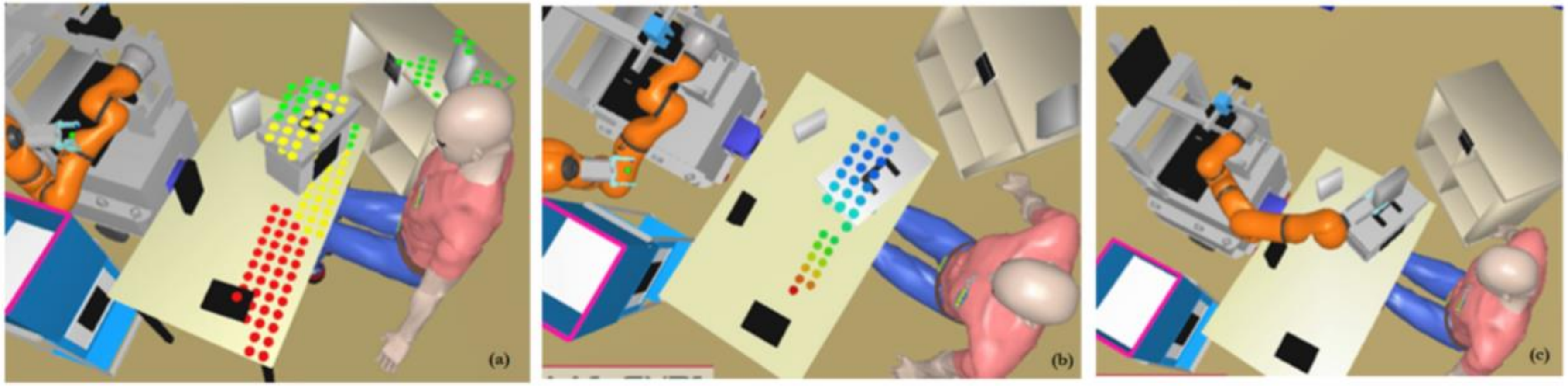

FIGURE 8 | Task of making an object accessible by the human to the robot (Pandey et al., 2013): **(a)** Places on the support planes where the human can put something with least effort. **(b)** Weighted points where the robot can support the human by taking the object. **(c)** The planner found a possible placement of the object on the box from where it is feasible for the robot to take. Note that, because of the object-closeness based weight assignment, this placement also reduces the human's effort to carry the object.

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Joint Human-robot action

FIGURE 9 | Initial state of the world in the Clean the table scenario. In this task, the robot and the human share the goal of cleaning the table together.

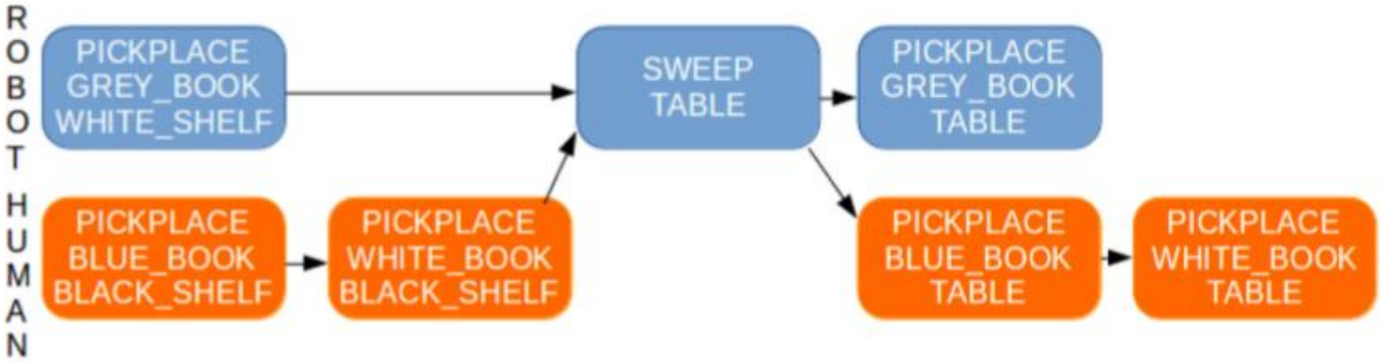

FIGURE 10 | Shared plan computed by the robot to solve the joint goal: first removing the three objects (books) that are located on the table, then sweeping the table in order to clean it and finally placing the objects back on the table. While cooperatively achieving the task, the robot will be able to detect and assess correctly why the human partner stays idle, for instance in cases where, due to a momentary absence, the human may have missed the fact that robot has swept the table.

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Joint Human-robot action

- This method leads to enlarged awareness ability, but:
  - ➢ Increased complexity and computational demand
  - ➢ This hinders the fluent operation of joint tasks
- Extensions of this work are still under investigation
- Promises big potential

Motivational System

- Implementing motivation for the robot
  - Consists of goals which are associated with rewards
    - Goals can be chained or individual
    - Goals can be permanently active or not
  - Goals are achieved through policies
- Motivational architecture:

1. Handles motivations
2. Computes possible policies for each motivation
3. Predicts the behavior of each policy and its effect on motivations
4. Predicts the effects of a chain of policies
5. Finds an optimal arrangement of the policies, using a reward maximizing function

Decision-making system

- Based on the Motivational system, a Decision-making system is organized in modules:
  - ➢ Intentional module, where objectives are in the form of motivations
  - ➢ Operational module, which computes policies
  - ➢ Deliberation module
- The Deliberation module is the “brains” of this model:
  - ➢ It provides the goal that will reward the operational model
    - o This in turn triggers the corresponding motivation, and creates policies
  - ➢ Then it computes the effects of these policies on all motivations

Decision-making system

- Deliberation module:
  - ➢ The policies are used to compute the maximum motivation reward sum
  - ➢ Lastly it hands this “policy agenda” to the supervisory system for execution
- In this way the robot:
  - ➢ Determines its goals by itself
  - ➢ Ponders how to satisfy its motivations in the most rewarding way
- This achieves a meta-reasoning capacity

Decision-making system

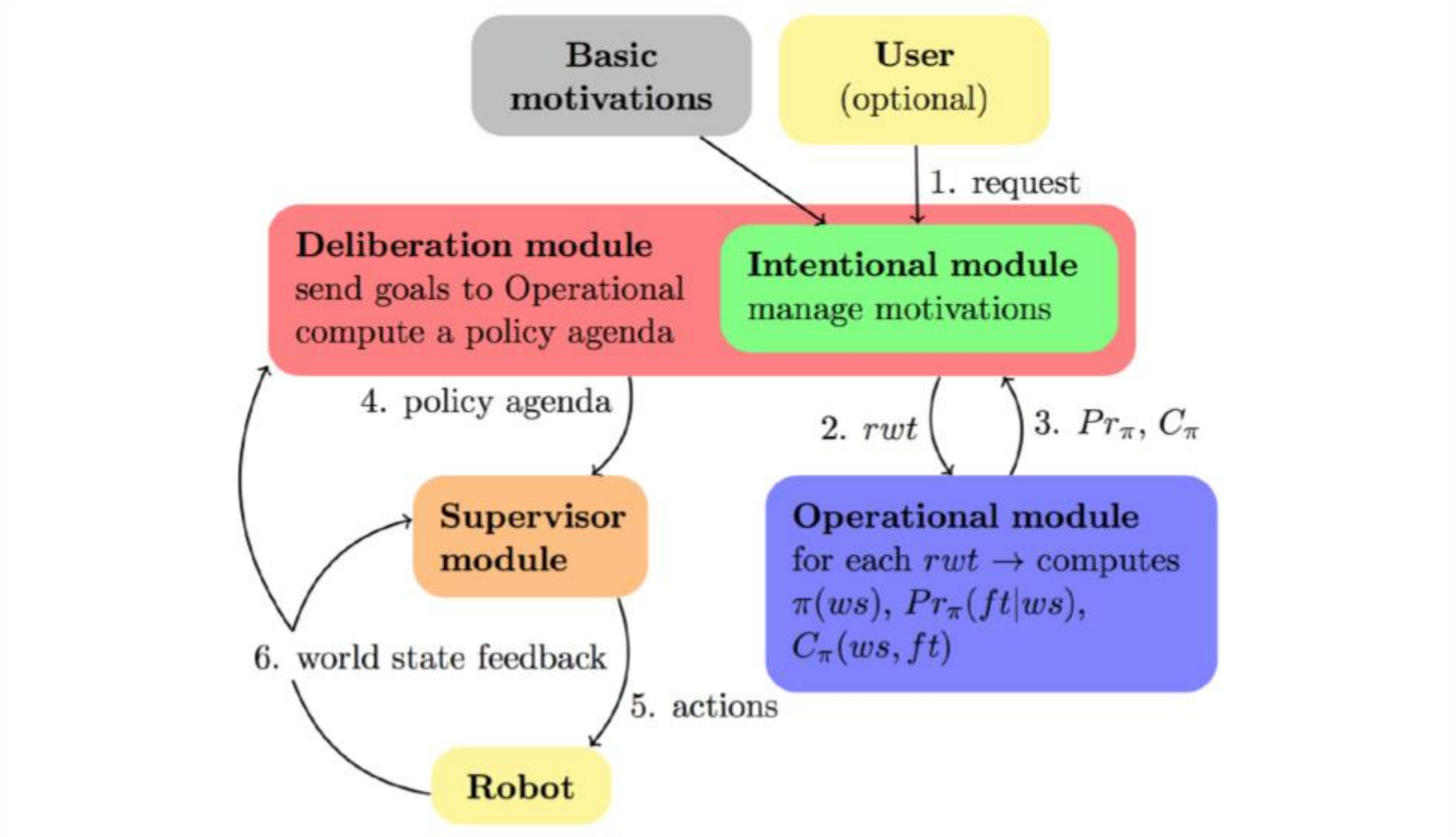

FIGURE 11 | Decision-making architecture including operational, intentional and deliberation modules. The deliberation module implements a meta-reasoning capability.

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The Cognitive Architecture

- This architecture unifies the systems and modules presented so far
- Made up of modules for:
  - Sensing and acting in the environment
  - Sensorimotor learning
  - Symbolic knowledge generation and management
  - Decision and action planning (Supervision system)
  - Controlling the modules (Motivation module)
  - Dialogue management

The Cognitive Architecture

- Sensorial perception module:
  - ➢ Contains the innate set of perceptual abilities for perceiving the environment
  - ➢ The Motor module contains the innate set of the robot’s actions
- Sensorimotor learning module:
  - Processes inputs
  - Discovers and learns interactions (i.e. affordance learning)
  - Generates new actions

The Cognitive Architecture

- Spatial reasoning and knowledge base modules:
  - ➢ Generate and store symbolic data about the environment, which is then used by the following modules
    - o Human-aware task planning module
    - o Human-aware motion and manipulation planning module
- Reinforcement Learning model-free decision making system:
  - ➢ Uses knowledge about the current state and available actions

The Cognitive Architecture

- Supervision system
  - ➢ Communicates with all the other modules
  - ➢ Decides which action planning system to deploy
  - ➢ Performs on-line correction of policies
  - ➢ Monitors the activity of interacting humans
- Motivation module:
  - Manages the robot's goals
  - Computes the optimal policy that leads to the highest reward

The Cognitive Architecture

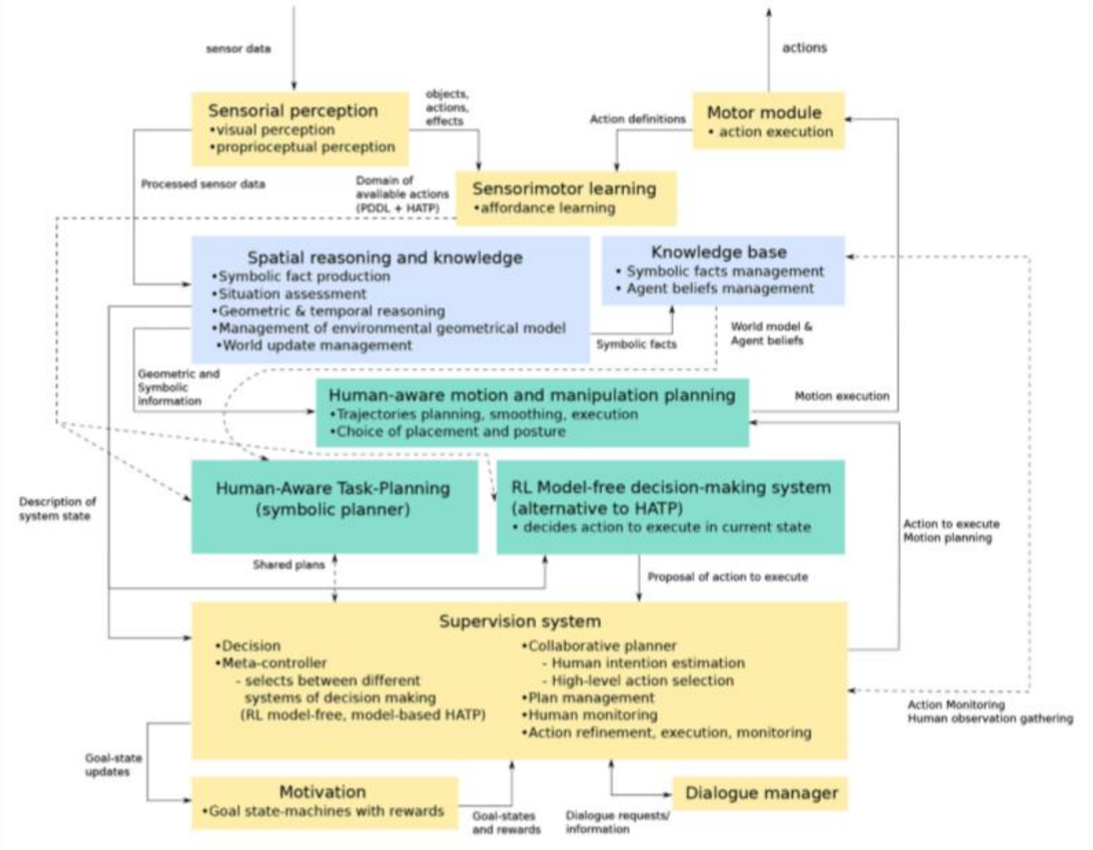

FIGURE 12 | The global cognitive architecture employed in the RoboErgoSum project. Blue modules are responsible for generating and managing the symbolic knowledge. Decision-making modules are shown in green. Solid and dashed lines are used only to improve diagram readability where lines cross, and are otherwise identical in meaning.

Source:https://www.frontiersin.org/articles/10.3389/frobt.2018.00088/full

References

1. Ulric Neisser (1988) Five kinds of self-knowledge, Philosophical Psychology, 1:1, 35-59, \\DOI: 10.1080/09515088808572924 https://doi.org/10.1080/09515088808572924
2. Chatila R, Renaudo E, Andries M, Chavez-Garcia R-O, Luce-Vayrac P, Gottstein R, Alami R, Clodic A, Devin S, Girard B and Khamassi M (2018) Toward Self-Aware Robots. Front. Robot. AI 5:88. doi: 10.3389/frobt.2018.00088 https://www.frontiersin.org/articles/10.3389/frobt.2018.00088/full
3. Schilling, K., De Lafontaine, J. & Roth, H. Autonomy capabilities of European deep space probes. Auton Robot 3, 19–30 (1996). https://doi.org/10.1007/BF00162465
4. The AI Revolution: The Road to Superintelligence, by Tim Urban https://waitbutwhy.com/2015/01/artificial-intelligence-revolution-1.html
5. Lukas Esterle, John NA Brown, Levels of Networked Self-Awareness DOI 10.1109/FAS-W.2018.00054 https://ieeexplore.ieee.org/document/8599561

Thank you for your attention!

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