Towards a Model for Tool-Body Assimilation and Adaptive Tool-Use

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***Abstract*— It is common experience that, through practice, tools disappear from our awareness. This form of perceptual learning occurs at all stages of life. In this paper we outline a model of "tool-body assimilation" and tool use inspired by recent findings in neuropsychology and neurophysiology. Our model is based on three assumptions: 1) the body schema is plastic and alterable and can extend to incorporate tools; 2) objects can be adapted *in-situ* to act as tools; and 3) tools are used on the base of their functionality. We evaluate our model by instantiating it in a simulated tool-using robot which learns to handle tools of various shapes to retrieve an object placed out of sight and out of reach. We discuss the model's plausibility to explain tool-body assimilation in humans and other tool-using primates.**

***Index Terms*— Tool-use; body image/schema extension; sensor fusion; contingency; adaptive robotics; embodied intelligence**

I. Introduction

It is often the case that through practice tools disappear from one's immediate awareness by becoming part of oneself or of the task [1], [2]. Sometimes, it is even possible to actually "feel" the object manipulated with a tool as if touched with the bare hand – an astonishing fact given that tools are non-corporeal, typically sensorless objects.

At least as astonishing is a finding that comes from a study showing that the judgement of subjective temporal order of taps delivered in rapid succession to our hands is inverted by crossing arms [3]. If the taps are delivered to the tips of sticks held in each hand the crossing of the sticks results in a similar reversal suggesting that the tactile signals are referred to the *tip of the sticks* [4]. This result finds empirical support in neurophysiological research on tool-using monkeys which examines the plasticity of a class of bimodal neurons in the monkey's intraparietal cortex [5], [6] (such neurons respond to both somatosensory and visual information originating from the monkeys' hands). Interestingly, after only five minutes (or less) of using a hand-held rake to retrieve distant objects, the visual receptive fields of the bimodal neurons expand to include the entire length of the tool used [5] (this happens even for video-captured images of the tool projected on a video monitor [6]).

These intriguing findings seem to indicate that the brain refers to the tips of the sticks (or of any other tool, for that matter) as if they were the hands. We deduce that humans and maybe also other primates "process" contacts through the hands and through tools in the same way. Tools act as mediators of kinesthetic and haptic sensation, so to speak. We call this cognitive capability "tool-body assimilation," or TBAS for short. In our daily lives many examples of TBAS exist. By way of illustration, imagine how to retrieve with a branch a coin that dropped to the floor and rolled under a vending machine (Fig. 1): we first search for the coin using the branch, then pull the coin closer to us, and finally reach for it with our unaided hand. We imply that some kind of TBAS is at work which helps to estimate the actual position, orientation, and shape of the non-visible coin with the branch.

Fig. 1. Blind retrieval task as an instance of tool-body assimilation. When retrieving a coin from beneath a vending machine, the contact between the "improvised" rake and the coin feels as originating from one's hand.

From the above discussion, we abstract three principles of tool-use which may be applied to the construction of a model of tool-body assimilation.

1) *Principle of sensory extension*: From an information processing point of view, we need to be able to detect the contact position and sense the contact forces between tool and manipulated object. Without access to such information, it is impossible to estimate the position of the object, to detect the contact, or to predict the motion of the object after contact. Nor would it be possible to plan or execute the necessary movements to handle the object.

2) *Principle of in situ adaptation*: Because we cannot

carry around at all times a toolbox and because there is no such a thing as a universal tool, it is often necessary to adapt objects found *in situ* as “improvised” tools.

3) *Principle of generalizable functionality*: The functionality of a tool needs to be “understood” independently of its form or shape. If we know how to apply a tool only to a particular object, generalization to an object found *in situ* is difficult – which conflicts with the principle of *in situ* adaptation. This suggests that a tool can have several meanings: the tool itself, the function that it can perform, and its potential role in achieving its user’s goal [7].

These principles crystallize in an extremely compact form intuitions that may be applied to the design of robots. Tool-use allows robots to extend their physical body structure and, consequently, their action space, and is thus regarded as a skill enhancing their autonomy. Many of the robots that use tools (e.g. [8]) are endowed with *a priori* knowledge about the shape and the inertial properties of the tools they wield. The knowledge is given to the robot by the designer implying that the robot does not comply with the principle of *in situ* adaptation. To the authors’ knowledge, there is still no robotic system which satisfies the three principles outlined above.

The paper is organized as follows. In Sec. II, we present a set of computational hypotheses derived from findings in physiology. In Sec. II-C and Sec. III, we first expose our computational model of tool-body assimilation, and then provide the details of its implementation. We describe the experiment and the obtained results in Sec. IV. Before concluding, we discuss the implications of our study for understanding adaptive tool-use in humans and other primates.

II. Computational hypotheses

In this paper, we make the distinction between primary tools and secondary tools. Whereas the former can be easily “internalized,” that is, incorporated into a neural representation of the body (e.g. a stick or a hammer), the latter are subject to their kinematic constraints and dynamics (e.g. a door knob). Some tools belong to both categories. For example, scissors represent a secondary tool when used to cut paper; when used as a stick, however, they are a primary tool. Because primary tools are more fundamental than secondary tools, here we deal only with primary tools.

In the rest of this section, we will formulate a set of hypotheses which we will use to motivate the model of tool-body assimilation described in Sec. II-C. The hypotheses were derived from recent neurophysiological and neuropsychological research: 1) Tools are assimilated and incorporated in the body representation; 2) tool-body assimilation co-occurs at the level of action, sensation and recognition; and 3) the spatial perception of the body is altered by synchronization of multiple sensory modalities.

A. TBAS in the brain

The brain contains multiple representations of the body. At the cognitive level, one can define two distinct and complementary definitions of body representation [9]: the body schema and the body image. While the former is a non-conscious neural map of the spatial relations among the body parts which integrates multi-modal sensory information, the latter is consciously manipulable and relates to the phenomenal experience of one’s own body (self-awareness). In the context of this paper, we will simply talk about “body representation” to indicate a neural representation integrating multisensory information about the body. It has been shown that tool-body assimilation of primary tools (which are physical extensions of the body), is caused by the incorporation of tools in such a body representation [10].

B. Three aspects of TBAS

We often use primary tools and our body in the same way. For instance, we are able to use either our hand or a rake to retrieve distant objects. Tools are not only adapted in terms of motion (kinematics) – think of a hammer, or a prosthetic arm or foot [1], [11] – but also in terms of sensation. In other words, sensory and motor adaptation co-occur. Such co-occurrence has been observed in humans or chimpanzees using tools [12], in horses with prosthetic feet [13], and in birds retrieving food with branches [14]. In terms of functionality, we can recognize tools and our body in a similar manner (e.g. we can “see” a hook as an alternative to our finger). It means we effectively abstract and generalize the functionalities of our body. Although motion, sensation and recognition differ from each other, they are also complementary which makes it hard to realize TBAS based on only one mechanism of adaptation. We thus hypothesize that TBAS relies on a multivariate stream of sensory information: with respect to motion, to sensation, and to recognition. Consequently, our computational model of TBAS will combine three coupled functional modules.

C. TBAS through synchronization

Bodily changes are recognized through alterations in the sensory stream. It is natural to ask what sensory information allows detecting bodily changes. There is a vast literature which examines the relationship between body representation and sensory integration. For instance, if a visual and a tactile stimulus occurring at different locations are synchronized, we tend to feel as if both stimuli originate from the location of the visual stimulus [15]. This illusion might be influenced by the preliminary learning of spatial and temporal relationships among multisensory information obtained by the body. Here, we note that the spatial perception of the body is altered by temporal synchronization between multisensory information. We hypothesize that coincidence (synchronization) plays a major role in detecting bodily changes and hence is an essential part of the adaptation of the body representation [16], i.e. the assimilation of primary tools into the body. sectionModel of tool-body assimilation

In this section we propose a computational model of TBAS which capitalizes on the three hypotheses exposed in Sec. II. The conceptual diagram of our model is illustrated in Fig. 2. According to the three principles of TBAS, tool-using agents need to be endowed with the following capabilities: 1) they need to be able to identify inertia parameters of tools, and 2) they need to be able to visually detect objects moving in congruence with their body. These two processes can be juxtaposed during a swing of the tool because they do not depend on each other (one being kinesthetic and the other visual). After the identification of tools, agents alter their body representation to adapt to the change caused by holding the tools. Such alteration enables agents to use forward models, "motion planners" or "generators" originally designed for their bodies, also for tools, and to exploit physical principles experienced by their body during tool use (see also principle of generalizable functionality).

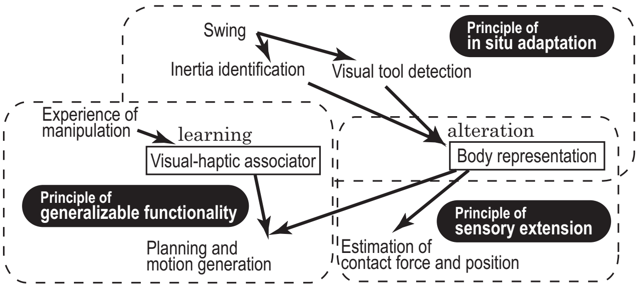

Fig. 2. Conceptualization of computational model of tool-body assimilation.

To simplify the discussion (see Fig. 3), let A be a tool wielded by the agent, let B be a goal object (e.g. the object to be retrieved), and let $\boldsymbol{r}_{\mathrm{o}}$ be the location of the hand on a body-centered coordinate system (the absolute coordinate system). We denote the location of the COG of A with the symbol $\boldsymbol{r}_{\mathrm{g}}$, and the contact point of A and B with $\boldsymbol{r}_{\mathrm{h}}$. During the contact, the force and the torque exerted by the hand on A are $\boldsymbol{f}_{\mathrm{o}}$ and $\boldsymbol{\tau}_{\mathrm{o}}$, respectively; whereas, the force and the torque which are exerted by B on A are $\boldsymbol{f}_{\mathrm{h}}$ and $\boldsymbol{\tau}_{\mathrm{h}}$.

D. Instantaneous sensory extension

From the principle of sensory extension follows that the agent needs to be capable of instantaneously sense contact locations and contact forces between tools and target objects. Here, the contact locations and contact forces are estimated from the kinesthetic response of the hand (force and torque), under the assumptions that 1) the tool is rigid objects and 2) the contact with a target object is a point contact, i.e. occurs only at one location (Fig. 3).

As can be shown analytically in this simple case (we omit the derivation), the agent is not able to compensate for the dynamics of the tool A without knowing its inertia parameters, that is, its mass m, its moment of inertia $\mathbf{I}_{\mathrm{g}}$, and the location of its COG $\boldsymbol{r}_{\mathrm{g}}$. Only if these parameters are known (see Sec. II-E), it is possible to obtain a straight "reference" line from the estimated force $\boldsymbol{f}_{\mathrm{h}}$ and the moment $\boldsymbol{\tau}_{\mathrm{h}}$. Although not biologically plausible, such a "line" is of computational importance because it allows to reduce the number of candidate contact points. In order to reduce this number further, the agent needs to know also the shape of the tool (such knowledge allows the agent to calculate the point of intersection between line and shape).

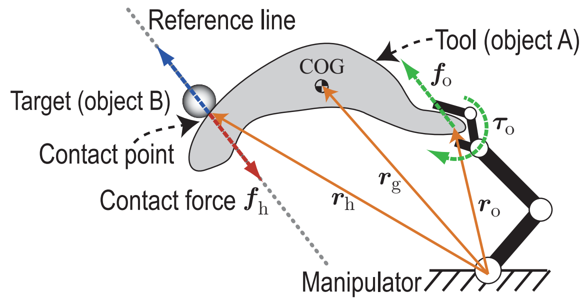

Fig. 3. Manipulator handling a rigid tool.

E. Identification of inertia parameters

As pointed out in the previous section, to simultaneously satisfy the principle of sensory extension and the principle of *in situ* adaptation, the robot has to be able to estimate the inertia parameters of the tool during swings. From the equations of motion of A, we can then derive the force $\boldsymbol{f}_{\mathrm{o}}$ and the torque $\boldsymbol{\tau}_{\mathrm{o}}$ which are a function of the tool's inertia parameters. The analytical solution is rather straightforward to obtain by solving the linearized version of the equations of motion of the tool (the derivation is omitted here for the sake of brevity).

F. Visual detection of tools

As mentioned above, for the model to work, the agent needs to know the shape of the tool. The shape is used to estimate the contact location and kinematic change by tool to control the tool; otherwise, it can not move the tool by feedforward. We assume that the agent obtains the shape of the tool visually. All moving objects extracted from vision do not physically connect to the body under normal conditions. The agent has to discriminate a tool (an object held in its hand) from other objects; because it needs to detect tools *in situ* from a set of objects presented visually.

A better way for the agent is to use synchronization between the motion of the body and the multiple objects. Any location $\boldsymbol{r}_{\mathrm{a}}$ on the handled object A can be expressed in the absolute coordinate system as $\boldsymbol{r}_{\mathrm{a}} = \boldsymbol{r}_{\mathrm{o}} + \mathbf{R}_{\mathrm{o}}\boldsymbol{l}$. This equation means that $\boldsymbol{r}_{\mathrm{a}}$ is a linear function of variables that can be acquired: the position of the hand $\boldsymbol{r}_{\mathrm{o}}$ and the rotation matrix $\mathbf{R}_{\mathrm{o}}$; $\boldsymbol{l}$ is a constant vector indicating $\boldsymbol{r}_{\mathrm{a}} - \boldsymbol{r}_{\mathrm{o}}$ in the hand-centered coordinate system. By exploiting such linearity the agent can "decide" whether an object is a tool by simply calculating the time-correlation between the translational and rotational velocities of its hand and each visible object. The time-correlation can be obtained with correlation analysis, or synchronization detection between variables.

Once the agent has extracted the objects (tools) to which it has to pay visual attention, it will be easier to acquire the shape of the tool used. As for motion control, it also enables to learn the kinematic change of a part of its body by holding the tool because there is a simple affine relationship between the locations of the hand and the held tool, whose parameters are easily identified.

G. Generalizing functionality

The principle of generalizable functionality postulates that the functionality (meaning) of a tool is independent of its physical appearance, i.e. shape or form. It is such independence that allows the agent to plan and execute movements of the tool as if it was part of the body. The implication is that although the body representation changes, the knowledge of functionality remains unaltered.

In the blind retrieval example given in Fig. 1, the agent has to first learn how a target moves through haptic feedback only. Such learning of motion change by contact is essentially a problem of sensory integration. The agent perceives contact forces only when it directly touches another object; meanwhile, motion of the object should be determined without any physical effect on it. Assuming that this can be done by vision (non-contact sense), generalizable functionality becomes a synonym of integration of visual and tactile information. We thus implement a module called visual-haptic associator (Fig. 2).

III. Experimental Setup and Model Implementation

To evaluate our model, we start by defining a task similar to the one represented in Fig. 1. In this task TBAS seems to play a crucial role. We implement each function in our computational model and instantiate it in a simulated robot.

A. The robot and its task

The robot is equipped with a camera unit (128x128 pixels resolution) and a 3-DOF planar manipulator to which various primary tools can be attached. The working space of the robot is a semi-circular area located in front of the robot (the robot, its working space, and the tools used are shown in Fig. 4). The task that the robot needs to solve is a "blind retrieval task" – an abstraction of the example given in Sec. I (Fig. 1) – in which the experimenter hides a target object under an opaque screen (the "blinder"). To solve this task, the robot has at its disposal a set of five tools whose characteristics are *a priori* unknown to the robot. The robot's manipulator is covered with a large number of tactile sensors (allowing it to detect contact with a high precision), and endowed with angular as well as kinesthetic sensors located in each joint. A movable target object is placed out of the robot's field of view and out of its reach. The motion of the target object is constrained to the working plane. The only means by which the robot can determine the location of the target is by poking it with its end-effector or with any of the available tools. The task is declared accomplished when the target is successfully retrieved or when the robot "discovers" that the target does not exist or is out of reach of the tools.

B. Identification of tool and target object

Because the tools move while the robot is wielding them, it is possible, by comparing the motion information originating from the tools with the one of the body, to segment the tools from the background. The robot extracts and tracks the objects in its field of view through a background image subtraction scheme (to segment objects from the background, the flood fill algorithm [17] is used). The resulting objects are then further processed, and the following features are estimated: the object's center in absolute coordinates (COF), its color, and the direction of its principal axis.

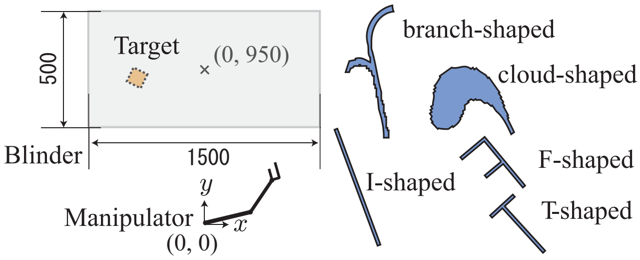

Fig. 4. Experimental setup consisting of manipulator, blinder, target object, and available tools. The units are [mm].

The time-correlation between essential variables of the tracked objects is then calculated (the object's color is used for the tracking). This operation is realized via the canonical correlation analysis (CCA) [18]. Any object that has a high correlation is regarded as a tool and its contour is approximated by a polygon which is then incorporated in the robot's body representation (which is realized as a list structure).

The robot first estimates the inertia parameters of the tool by solving the tool's equations of motion. Using the identified inertia parameters, the robot can obtain the contact force f_h between the tool and the manipulated object. Moreover, it can estimate the locations of the candidate contact positions with respect to the origin (reference line). The robot then calculates the intersection between the reference line and the registered shape of the tool, and, based on the intersection point, thus reduces the number of candidate contact points to a finite number. Utilizing its action history, the robot can decrease the number of candidate points even further. The estimated contact position and force is eventually fed to the visual-haptic associative memory (Fig. 2).

C. Associative memory

The estimation of spatial information from haptic cues is crucial in the blind retrieval task. Assuming constant gravity and friction, it is easy to show that the displacement of the target is essentially proportional to the energy supplied to it by the "force impulse" $\boldsymbol{f}_{\mathrm{h}}\,\delta t$ and the "torque impulse" $\boldsymbol{\tau}_{\mathrm{h}}\,\delta t$. According to this consideration, we implement an associative memory which associates the square of the force impulse $\boldsymbol{f}_{\mathrm{h}}\,\delta t$ and displacement. Given a "force impulse" $\boldsymbol{f}_{\mathrm{h}}\,\delta t$ and $\boldsymbol{\tau}_{\mathrm{h}}\,\delta t$, it is therefore possible to recall the estimated displacement of the target.

The relationship between the displacement and kinesthesis is a function of the postural state of the target. The robot treats the output of the memory as a probabilistic field. Finally, it can estimate the existence probability of the target by using the measured contact force and torque.

D. Motion planning and generation

The robot's controller relies on a model of the manipulator's kinematics, a planner and a movement generator (although not done here, one could endow the robot with means to learn the model). All functional modules are realized by resorting to standard robotic techniques. For instance, the adopted path planner is RRT-connect [19]. The robot is endowed with an "innate" motion strategy, which sweeps the manipulator over a region in which the target object is likely to be found. Force impulses applied to the object during a retrieval action are fed to the associative memory, and are used to estimates the probability that the target is in a particular region. The robot checks systematically all faces of the tool (the tool is approximated as a polygon) in terms of closeness from the center of the likelihood map, and based on the result decides whether to use the face for a retrieval action.

IV. Experiments and Results

All experiments begin with the specification of a tool, which is put in the robot's hand by the experimenter. To identify the tool, the robot first swings the tool for approximately 5 *sec* (Fig. 5), and calculates the CCA between the sensory information associated with the movement of the hand and of each object obtained through tracking. Only in the case of "handled" objects is the movement of the body correlated with the movement of the object. In other words, the correlational values are high and the object can be detected as a tool – the correlation for the moving box decreases after a while (see "contingency check" in Fig. 6). Subsequently, the robot extracts the contour of the tool, and incorporates the resulting polygonal shape into the body representation (by extending the list structure defining it). Concurrently, the robot identifies the inertia parameters of the tool (mass, moment of inertia and COG). Such identification is accurate and is done with an error bound to below 1%.

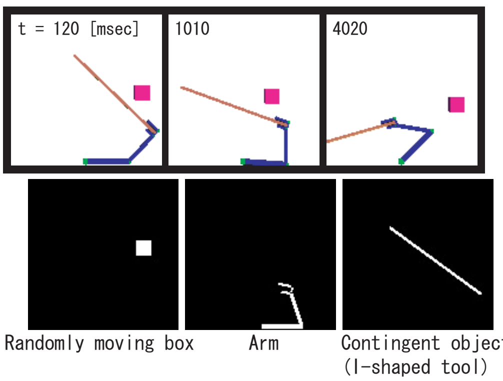

Fig. 5. Top: robot wielding I-shaped tool. Bottom (from left to right): object moving in round path, manipulator, and tool.

The robot solves the blind retrieval task with the shape and inertia properties obtained above, and with a previously learned associative memory which maps visual and haptic information. The results for four different tools are reproduced in Fig. 7. As evident from the figure, for each tool,

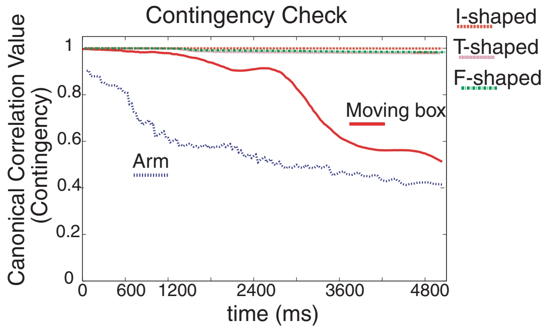

Fig. 6. Contingency check via canonical correlation as a function of time.

the robot successfully solves the blind retrieval task. The figure also shows that the movement sequence generated for retrieving the target depends on the shape of the handled tool. The branch-shaped tool allows quasi-grasping; the cloud-shaped tool retrieves the object in one single "shot" (this latter tool is heavy and $\boldsymbol{f}_{\mathrm{h}}\,\delta t$ is thus quite large).

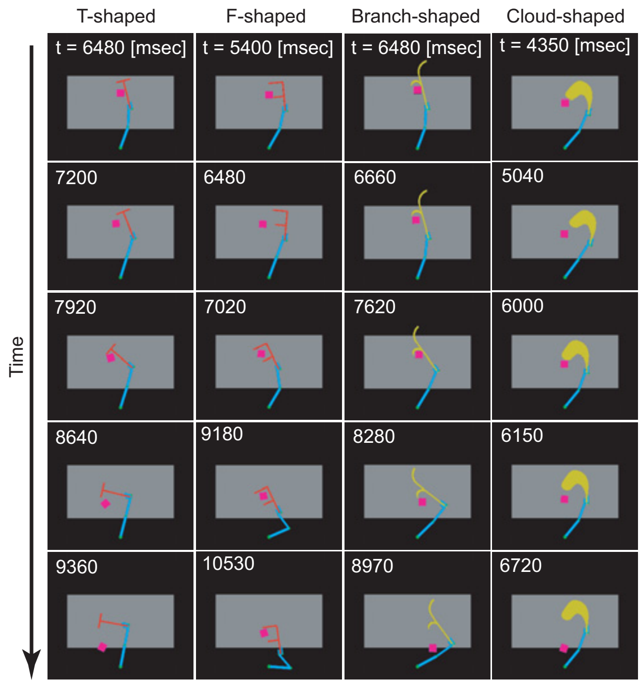

Fig. 7. Blind retrieval with T-, F-, branch-, and cloud-shaped tools. The gray rectangle indicates the "blind" zone.

Another significant result is displayed in Fig. 8. The snapshots show how the likelihood of an object occupying a specific position changes over time (the object is hidden under the blinder). After the first contact between tool and target object, the uncertainty concerning the object location decreases drastically. This is done by feeding the estimated contact impulse $\boldsymbol{f}_{\mathrm{h}}\,\delta t$ and position $\boldsymbol{r}_{\mathrm{h}}$ to the associative memory which return the possible target region after the contact. Doing the retrieval motion against the possible region derived from the given strategy, the estimated region gradually moves to the center of the body. Finally, the blind retrieval tasks are accomplished.

Our results indicate that TBAS is crucial for solving the blind retrieval task. Estimating the contact location (the location of the target object) on the held tool from the kinesthetic response of the hand, the robot can do efficient retrieving motion.

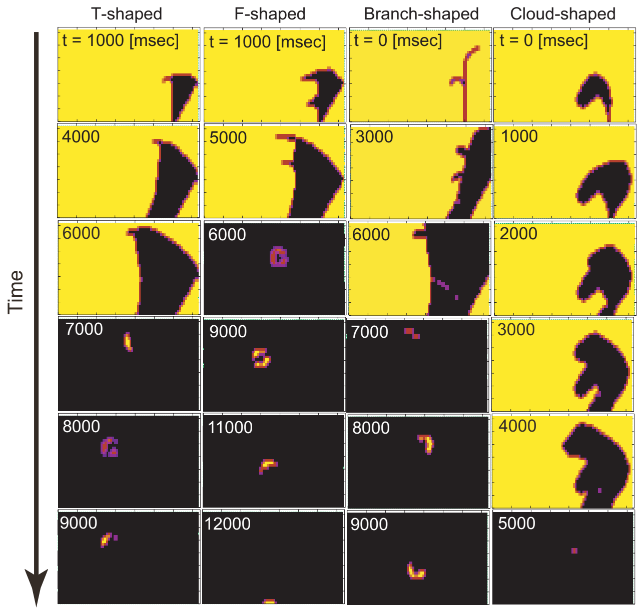

Fig. 8. Likelihood of object location over time during blind retrieval using T-, F-, branch- and cloud-shaped tools (from top to bottom). The bright (yellow) tiles correspond to a high likelihood; the dark tiles to a low likelihood.

V. Discussion

We proposed a model of tool-body assimilation (TBAS) which capitalizes on three principles of tool-use: 1) the principle of sensory extension; 2) the principle of *in situ* adaptation; and 3) the principle of generalizable functionality. The central issue of the model is the identification of the shape and of the inertia parameters of the tool used. By incorporating these parameters into its body representation the robot can use different tools to solve the same task. We instantiated our model in a physics-based simulated robot. The robot adaptively completed a blind retrieval task using a set of tools which were *a priori* unknown. Our experimental results provide "synthetic" support for our model of TBAS, and shed light on the type of information processing necessary for TBAS to occur.

The model of TBAS validate the three computational hypotheses put forward based on physiological findings. Are we allowed to say, however, that the implemented functional modules are biologically plausible? Support for the identification of the inertia parameters comes from a phenomenon called "dynamic touch" during whose occurrence humans seem to perceive the length of an object through inertia parameters estimated through kinesthetic response on our hands [20]. Detecting objects synchronized with the body motion in vision is particular to humanoid apes, who can recognize mirror images of their bodies [21]. From these findings, we deduce that our model and its functional modularity have some biological plausibility and synthetically explain our capability of the TBAS.

In our experiments, various tool-dependent ways of retrieving a distant object emerged. These emergent tool-using behaviors allow us to hypothesize that agent-environment interaction plays a fundamental role in recognizing functionality and usability of tools *in situ*. We emphasize that this abstraction is a "higher-level form" of tool-use as compared for instance to object manipulation through touch. The modeling of autonomous recognition of tool functionality will be addressed in future work.

We conclude by noting that although this study represents a step forward, the mechanisms underlying TBAS *in vivo* remain largely unknown.

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