

The Ideomotor Principle Simulated

An Artificial Neural Network Model for Intentional Movement and Motor Learning

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Abstract: Although the ideomotor principle (IMP), the notion positing that the nervous system initiates voluntary actions by anticipating their sensory effects, has long been around it still struggles to gain widespread acknowledgement. Supporting this theory, we present an artificial neural network model driving a simulated arm, designed as simply as possible to focus on the essential IMP features, that demonstrates by simulation how the IMP could work in biological intentional movement and motor learning. The simulation model shows that IMP motor learning is fast and effective and shares features with human motor learning. An IMP extension offers new insights into the so-called mirror neuron and canonical neuron systems.

1 INTRODUCTION

The ideomotor principle (IMP) claims that the nervous system initiates voluntary actions by anticipating their typical sensory consequences (Kiesel and Hoffmann 2004, Stock and Stock 2004). Over the past twenty years increasing evidence favoring this theory emerged from both behavioral studies (reviews in Wulf and Prinz, 2001; Wohlschläger et al., 2003; Shin et al., 2010; Hommel, 2013) and fMRI studies (Eran Dayan et al., 2007; Melcher et al., 2008, 2013; Pfister et al., 2014). Unfortunately these findings centered on individual IMP features and they provided no overall view of a working IMP. Given this background, simulations with artificial neural networks (ANN) that demonstrate how the IMP works may lead to its wider acknowledgement. Although few reported simulations of this type explicitly mention IMP (Karniel and Inbar, 1997; Sauser and Billard, 2006; Butz et al., 2007; Galtier, 2014), many involve IMP's underlying rationale, namely sensorimotor mapping. Existing simulations nevertheless provide scarce help in understanding the IMP because they use non-IMP procedures, such as supervised learning or complicated modularity and flowcharts, or they add complex details that make the essential IMP features even harder to understand.

In this paper we take an opposite approach: to

highlight how the IMP works and make it easy to understand, we present an unsupervised ANN system that is as simple and basic as possible and learns to move a three-joint arm in a workspace using the IMP and sensorimotor mapping. We examine its main features and compare them with those of human motor learning. We then suggest how an IMP extension also offers new ways to look at the so-called mirror neuron system.

2 METHODS

2.1 Model Design

Our simulation consisted of an ANN controlling a three-joint simulated limb moving on a two-dimensional plane (Fig. 1). The network received on its input units sensory information on the limb position, and sent limb commands from its output units. Each limb movement was defined by three vectors: the initial sensory state (before the movement); the final sensory state (after the movement); and the neuromuscular activations needed to pass from the initial to the final state. The first two vectors were given to the ANN input units, and the ANN had to compute the third vector on its output units. Because IMP states that intentional limb movements depend on anticipation of their

sensory effects, the ANN input units receiving sensory information on the *final* limb state (S1 units) also received motor commands from a component outside the network that established where the moving hand should be positioned and therefore acted as Motor Will. Commands from it to the ANN consisted of sensory representations of the desired final hand position, coded as visuospatial coordinates in agreement with the observation that motion planning in human takes place in the visually perceived space (Flanagan and Rao 1995, Shadmehr 2005). Unlike S1 units, the ANN input units receiving sensory information on the *initial* limb state (S2 units) did not receive motor commands, they only received “proprioceptive” sensory information from the limb joint angles.

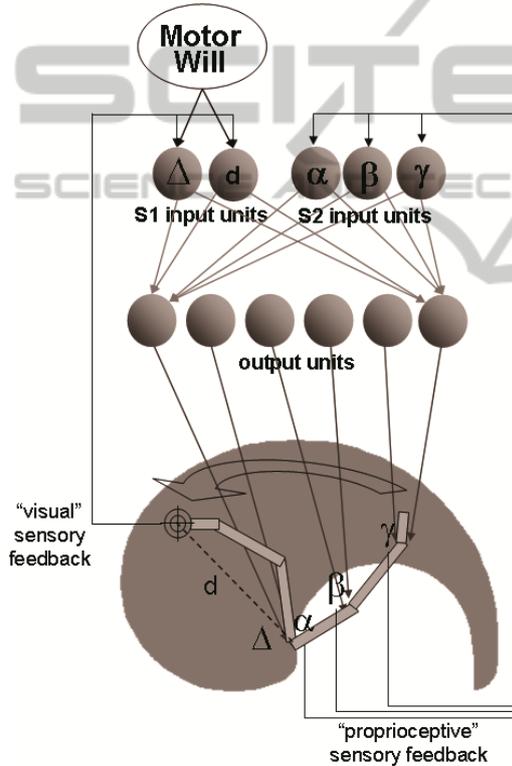


Figure 1: General architecture for the Ideomotor Principle (IMP) simulation model. The artificial neural network (ANN) controls a 3-joint limb moving in a two-dimensional plane. The ANN receives sensory feedback information on the limb and motor commands from Motor Will. Δ , d : polar coordinates for the hand (Δ = angle with respect to the posterior-anterior axis, d = distance from the shoulder point). α , β , γ : shoulder, elbow, wrist joint angle. Not all input-to-output connections depicted; actually each input unit sends connection to all output units.

Given that velocity information was not indispensable to the key IMP mechanism as long as the limb was assumed to start from still and end still,

we decided to give the ANN only sensory information about limb position (joint angles and spatial hand position), not velocity.

2.1.1 Limb

The limb was designed to represent a simplified model of the human right arm comprising three segments, “arm”, “forearm” and “hand” articulated with three joints “shoulder”, “elbow” and “wrist”, with the shoulder situated in a fixed point in space, and the hand able to move freely in the reachable space. The arm measured 70 pixels in length, the forearm 70 pixels and the hand 20 pixels (because the model involved a simulation displayed on a computer screen, for simplicity lengths are given in pixels). The three joints opened and closed within angular limits in a similar way to a human arm: the shoulder from 23 to 190 degrees, the elbow from 20 to 180, the wrist from -90 to 72. The overall area reachable with the hand (grey area in Fig. 1) therefore assumed a drop-like shape measuring 298 x 200 pixels.

The three joints were each controlled by an agonist-and-antagonist muscle couple. Each muscle was controlled by a neural network output unit. Muscle actions were simulated in a simplified manner, without recourse to spring models or tension-length diagrams. Analog outputs from 0 to 1 from the two units acting on muscle flexion and extension for every joint were assumed to determine variations in joint opening or closing according to the following equations:

$$a_{i,t+1} = a_{i,t} + (e_{i,t} - f_{i,t} + p_{i,t}) / m_i \quad (1)$$

$$p_{i,t} = [(amax_j + amin_j) / 2 - a_{i,t}] \cdot k_j \quad (2)$$

where:

$a_{j,t}$ = degree of joint j opening at time t , in radians;

$e_{j,t}$ = output (0 to 1) from the unit controlling the extensor muscle for joint j at time t ;

$f_{j,t}$ = output (0 to 1) from the unit controlling the flexor muscle for joint j at time t ;

$p_{j,t}$ = passive elastic muscle and ligament force acting on the joint j , maximum when the joint is fully opened or closed;

m_j = mass in the segment distal to the joint j , normalized for the upper arm (1 for the upper arm, 0.6 for the forearm, 0.2 for the hand);

$amax_j$ = degree of maximum opening for joint j , in radians (1.05 for the shoulder, 1 for the elbow, 0.4 for the wrist);

$amin_j$ = degree of maximum closure for joint j , in radians (0.13 for the shoulder, 0.11 for the elbow, -0.5 for the wrist);

k_j = force intensity $p_{j,t}$ for the joint j , empirically chosen (0.5 for the elbow and shoulder, 0.14 for the wrist).

2.1.2 Neural Network

The ANN was a two-layer neural network comprising 5 input units and 6 output units, fully connected with anterograde connections from input to output. There were no hidden units. The input units were simple linear units. The output units were classic sigmoid units, having an analogic output ranging from 0 to 1 and equipped with modifiable learning bias. Their output values were copied into equation (1) (variables $e_{j,t}$ and $f_{j,t}$ for any joint j) to compute limb movements. The first two input units (S1 units) received “visuospatial” information on the hand position, encoded in polar coordinates (angle in radians with respect to the posterior-anterior axis and distance from the shoulder, normalized for the overall length of the fully extended limb). The last three input units (S2 units) received “proprioceptive” information on the opening angle for each of the three joints, normalized between -1 and 1. Before each movement the two S1 units also received commands from Motor Will.

2.2 Simulation Flow

When the simulation began, the connection weights and the output unit biases were initialized with random values ranging from -0.25 to +0.25. The arm was positioned with all the joints partly opened. After the initialization stage, the simulation proceeded in turns, each turn comprising the two phases, movement and learning, each comprising three steps.

2.2.1 Movement

1. The input units received sensory information from the arm: S1 units received the spatial location of the hand, and S2 units the angles from the three joints.
2. Motor Will overwrote S1 input unit activations with activations corresponding to a random desired hand position.
3. The input units activated the output units, and the joint opening angles therefore changed according to equations (1) and (2). The actual output values were recorded for use in the ensuing learning phase, during which they yielded the desired output, *target activations*. The difference in pixels (spatial errors) between the desired hand position (*target position*) and the hand position actually reached, were

measured and recorded. This spatial error measurement served only to evaluate network performance and not to assess motor learning.

2.2.2 Learning

1. The sensory pathways conveyed to the S1 units information on the new hand position.
2. The input units activated the output units again, this time using the new activation values obtained from the S1 units corresponding to the hand position actually reached. These outputs left the joint angles unchanged, they served only for learning. These new outputs were the ones the network would produce if the desired movement were actually the movement achieved in movement phase 2.2.1, step 3. The difference between the current outputs and the outputs recorded in that phase was the error to minimize during learning.
3. A standard delta rule (Rumelhart, Hinton & Williams 1986) was applied to minimize the error vector calculated in the former step. The results we describe were obtained with a learning rate = 0.1 and momentum = 0.25.

2.3 Tests

Besides evaluating the “online” spatial error after every movement (section 2.2.1 step 3), after every 5000 movements the program temporarily stopped the simulation, and submitted the network to an “offline” test entailing a predefined set of 588 movements (Fig. 2A) commanded by the Motor Will transmitting to the S1 units the polar coordinates for the 588 successive turns. During testing, the learning phase (section 2.2.2) was skipped. For each of the 588 test movements the position actually reached by the hand and the corresponding spatial error were recorded for later evaluation offline.

We used these procedures to conduct several simulations. In some simulations we introduced a sort of “sensory blind spot”, a wide circular area, covering up to 50% of the workspace and differentially positioned in the various simulations (Fig. 3A), where we skipped the learning phase (2.2.2) when the hand ended up in this area.

In other trials, to assess whether learning depended on precise physical values inherent to the system, and to verify whether the controller system adapted to changes in the controlled system, we varied the sensory code used for hand position or the limb segment mass (variable m_j in equation 1), right from the beginning, or after advanced learning (30000 movements).

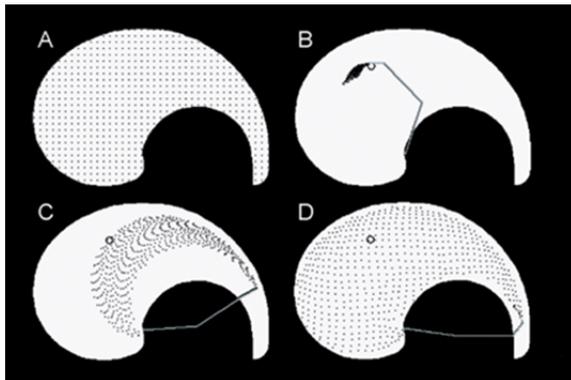


Figure 2: Progressive improvement in performance during the 588 test movements with motor experience. Small circle = hand starting point; black points = hand movement arrival point. A: target points; B: points effectively reached before learning; C: after 5000 random movements and D: after 30000 random movements.

3 RESULTS

In all the simulations the tested ANN system improved from a mean spatial error of more than 150 pixels when simulation began to an error of less than 15 pixels after 10,000 movements (few tens of seconds on a modern pc) and fewer than 7 pixels after 30000 movements. These results underwent minimum variability owing to random elements used for initializing weights and movement choices decided by Motor Will.

The network's motor performance, as assessed with periodic testing using the 588 target points, progressively improved with experience, improving from a mean spatial error of about 95 pixels at turn zero (Fig. 2B) to 53 pixels at turn 5000 (Fig. 2C), and 13 pixels at turn 30000 (Fig. 2D) (these values differ from those for the mean spatial error mentioned above because they only refer to the 588 test movements instead of all movements). Before motor learning started, the points effectively reached clustered in an area corresponding to the intermediate arm positions (Fig. 2B). As the network acquired experience, arm movements gradually expanded and after 30000 movements covered the workspace in a fairly uniform manner (Fig. 2D) acceptably matching the targets.

After 30000 movements, spatial error distributions showed that the system performed well over the whole workspace, except in the extreme tail in the drop-shaped area corresponding to extreme extension (Fig. 3B). The sensory blind spot had scarce influence on learning improvements (Fig. 3C,D). These results remained uninfluenced by the

hand sensory code used, nor did they significantly suffer from mass changes in limb segments, before or after motor learning.

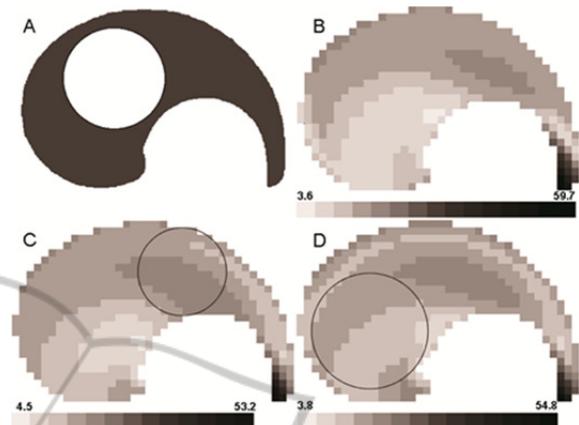


Figure 3: Spatial error distribution for the 588 test movements after 30000 random movements with and without no-learning areas ("sensory blind spot"). A: workspace area (dark grey area) with a generic blind spot (white disk); B: errors (in grey color code) without the sensory blind spot; C, D: with the sensory blind spot (black outline circle) in two different sizes and positions. Values are for spatial error in pixels.

4 DISCUSSION

4.1 Comments on the Model

The simplified ANN simulation, focusing on the basic IMP features insofar as motor commands and sensory feedback reach the same S1 input units, effectively learned to move the arm in the workspace. It learned acceptably well even when we varied influential experimental variables such as the sensory code used for hand position, the mass for the limb segments to move, and when the ANN was able or unable to receive sensory feedback about movements performed in the workspace (sensory blind spot). Our decision to disregard velocity sensory information or hidden neural network units had no apparent influence on our model's functional ability thus confirming that these variables are unessential to model functioning.

Our IMP model reproduces with acceptable approximation the various human motor learning properties, such as learning from experience, ability to work regardless of the specific body segment features, ability to adapt to changes in these features, and the fact that even randomly-generated movements contribute to learning (infantile motor babbling). Like the human motor learning system,

our ANN underwent completely unsupervised learning. We never used external sample sets. The ANN itself generated learning examples from its random movements and errors. For learning we never measured spatial errors between the desired movements and those actually made. Conversely, as the learning error we used the difference between output unit activations in two different functional phases (phase 2.2.1 step 3 and in phase 2.2.2 step 2), values completely and locally available to the net.

In our proposed model *the movement learned is not the desired movement but the movement effectively done* (section 2.2.2). The system nevertheless succeeds in performing with reasonable precision even movements never previously done (the 30000 learned movements taken as a typical number of movements for simulation are less than a mere 0.0001% of the over 300 million movements possible in the workspace, and the test movements described in section 2.3 and those finishing in the sensory blind spot were even explicitly excluded from learning). This system ability evidently stems from an ANN's well-known ability to generalize (Caudill & Butler 1992), a feature allowing our ANN to interpolate and extrapolate information from the movements done, thus filling in unexplored movements and forming the general sensorimotor map valid for all movements.

Even though these model features are biologically plausible, other features are biologically less plausible, at least with the essential model architecture we used. For example, in particular, the proposed learning system requires special timing. After the movement, when sensory feedback from the hand position returns to the S1 units, the S2 units must still retain information on the limb state before the movement, and the output units must still retain information about the activation that caused the limb muscles to contract. Hence during learning, the network must have constantly available all three components mentioned in section 2.1: neuronal activations coding the initial limb state, the final state, and those causing the limb to pass from its initial to its final state, that we will henceforth call *learning triplets*, or simply *triplets*. In a computer software algorithm this requirement poses no problems whereas in biological nervous systems it raises several concerns. A more realistic model to simulate a biological motor system should therefore include accessories such as memory units and units that regulate activation flow to and from the network. These accessories become even more essential as the possible time shift between the three

triplet components increases, as it does in the extended model we propose in the next section.

4.2 Triplet Chaining

The model we propose here extends IMP from elementary movements to more complex behaviors thus unifying the various intentional movement scales under a single principle. The ANN model we have examined so far applies to elementary movements. Conversely, the chained triplet model can also account for more complex actions, where it can also provide a new insight into neuronal populations such as canonical neurons (Shepherd 1992) and mirror neurons (Di Pellegrino et al. 1992; Casile 2013) that have been found in biological nervous systems and whose real function remains debatable.

The extended triplet model that we propose here involves several triplet-networks, linked so that the output units for each preceding triplet-net also act as the S1 input units for the ensuing triplet-net. The S1 and S2 input units can receive sensory information not only from the osteo-muscular system, but from the whole body and external environment. In this chain, the S1 input units on the first net receive the actions desired by Will (actions that are more abstract than the simple and concrete desire to bring the hand to a desired position), and the ensuing nets progressively increase the level of detail and concreteness for the actions needed to satisfy the desire. Finally, the final net (the net described in the basic model) generates the neuromuscular activations required to perform the selected action(s).

For example, if a person is hungry and sees an apple at hand, the S2 units for the triplet-nets in the chain receive this information as the actual/initial state. If Will generates and transmits to the first net's S1 units the desired state "no longer hungry", then the first net, which has learned from experience that when one is hungry the action for curbing hunger is to eat, generates the sensory-coded desired action "eat" as activations on its output units. These output units in the first net are also the S1 input units in the second net, so "eat" becomes the final desired state (in this case a desired action) for the second net.

The second net has learned from experience which objects are edible, and when the desired action is to eat and the object is edible, it generates on its output units the sensory-coded action "eat the object", which becomes the desired action for the third net S1 units.

Having learned from experience that when faced with an apple and a desire to eat it the action to eat it is to get it, the third net now generates on its output units the sensory-coded action “get the apple”, which becomes the desired action for the fourth net.

“Get the apple” is still sensory encoded though, so it actually pictures “arm extended to the apple and fingers tightened on the apple”. This is the desired final state for the fifth net, the net described in the basic model, the one that also receives on its input units sensory information about the current arm state and activates the arm muscles.

Essentially, we suggest that in the nervous system voluntary actions or behaviors are triggered by formulating their end-effects as high-level sensory representations of the desired results. These representations are generated in the prefrontal cortex, especially in the dorsal and lateral prefrontal areas (Haber 2003; Watanabe & Sakagami 2007; Tanji & Hoshi 2008). These areas act as a high-level, ‘strategic’ Motor Will by generating sensory representation for the desired result (goal), without focusing on details in its execution, other than possibly enforcing context-related constraints (e.g. to avoid an obstacle in grasping an object).

These sensory representations consist of neuron activation-and-inactivation combinations in the prefrontal areas, which in turn evoke sensory representations in the frontal premotor areas and in parietal, occipital, and temporal sensory and associative areas. These parietal, occipital, and temporal areas encode both sensory-specific representations for the goal (symbolized by the S1 units in our model) and actual sensations from the body and the environment relevant to the task (symbolized by the S2 units in our model). These representations and sensations are locally sensory-specific: tactile or proprioceptive in the parietal lobe, visual in the occipital lobe, and acoustic or visceral in the temporal lobe. Unlike these areas, the premotor areas encode the goal in a more abstract and multisensory way. Premotor area neurons are S1 units in our model. Other S1 and S2 units are probably located in sub-cortical structures, especially in the basal ganglia (S1 units) and the thalamus (S2 units).

All these representations then travel throughout these areas, converging towards the primary sensory (S1, postcentral gyrus) and motor (M1, precentral gyrus) areas and the sub-cortical motor structures through subsequent elaboration steps, represented in our model by the chained triplets that progressively detail the appropriate elementary actions needed to reach the goal. These representations gain motor

detail as they converge to the S1 and M1 brain areas. Until the very last step, the first and only one that really encodes the former sensory action representation into the motor effector (neuromuscular) space, all these representations are sensory-coded. The neurons making the final sensorimotor translation (the output group in our basic model) are probably located in sub-cortical motor structures, or even in the spinal chord.

This model is consistent with increasing evidence from motor research in primates and humans (reviews in Lebedev & Wise 2002, Graziano 2006, Cisek & Kalaska 2010. See also Miller 2000, Miller & Cohen 2001, Haber 2003, Tanji & Hoshi 2008 for specific reviews on the role of the prefrontal areas in voluntary movement; Rizzolatti & Luppino 2001, Rozzi et al. 2008, Koch et al. 2010 for the role of parietal areas; Burnod et al. 1999 for flow and distribution of movement-related sensory representations; and Zinger et al. 2013 for the functional organization of information flow in the corticospinal pathway and joint specificity of M1 sites). The stages progressively elaborating and subdividing motor goals into triplet-nets are not necessarily exactly those we describe. What our simplified model allows us to conclude is that the general features underlying triplet network chaining concord well with current knowledge on intentional movement.

Along the triplet chain, the role and function of some known as well as elusive neuron populations become clearer. In particular, the function of the second network in the chain reasonably recalls known canonical neuron properties. The function of the third network recalls known mirror neuron properties, at least those described for certain major mirror neuron subpopulations, which seem essentially to encode the subject’s ability to interact with objects (Caggiano et al. 2009, 2011; Casile, Caggiano & Ferrari 2011) and reasons for grasping an object (Casile, Caggiano & Ferrari 2011). Hence the interpretation our sensorimotor model offers for mirror neurons is that they primarily exist to allow us to move intentionally, being a step in sensorimotor mapping that descends from general, high-level sensations (“I am hungry”) and Will-desired sensations (“no longer hungry”) to the actions (“get the apple”) able to make the desired sensations real. This is a more basic and critical function than functions other explanations propose, for example that mirror neurons are essential for learning by imitation, for the theory of mind, or for empathy (Gallese & Goldman 1998; Gallese 2001; Gallese, Eagle & Migone 2007; Iacoboni 2009).

These earlier conjectural explanations remain unproven and highly controversial (Borg 2007; Hickok 2009; Dinstein et al. 2010; Heyes 2010; Decety 2011; Lamm, Decety & Singer 2011) and are somewhat disconcerting when we consider them in the monkey, the species in which mirror neurons have been primarily found. Conversely, more recently emerging findings (Caggiano et al. 2009, 2011; Casile, Caggiano & Ferrari 2011; Casile 2013) seem in line with the model we propose, insofar as they showed that many mirror neurons exist to encode the subject's interaction with objects, rather than similar interactions by others. These "special" mirror neurons and the classic mirror neurons that *also* respond to seeing "their" action performed by others should be considered together rather than individually. Hypotheses considering single neurons isolated from neuron combinations should be regarded with caution, especially given that the only study that demonstrated mirror neurons in man (Mukamel et al. 2010) found confusing and even contradictory individual neuron responses.

5 CONCLUSIONS

Our unsupervised ANN simulation confirms, as the IMP claims, that voluntary actions can be initiated by imagining (desiring) their sensory effects. IMP seems a valid model for understanding human sensorimotor mapping, intentional movement and motor learning. Detailing and extending the IMP in what we termed the "chained triplet-net" model makes the IMP also helpful in explaining voluntary behavior besides elementary actions. Along this chain, elusive neuronal systems such as the canonical and mirror neuron systems acquire definite meanings. Future research should endeavor to identify which other non-motor nervous functions, such as cognitive functions, the extended IMP and the triplet model might help to explain.

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