



# Prosthetic hand signals

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How Bayesian inference can decode movement intentions and control the next generation of powered prostheses. By **Mike Wininger** and **Reva Johnson**



**A**s you read these words, your hand is performing a continuous choreography of postures that fluidly execute your desired actions – whether that be holding the magazine steady, tilting it slightly to avoid the reflected glare of an overhead light, or creasing the corners in preparation to turn the page. To execute these actions, your brain monitors streams of information from internal and external sources, and sends commands to your muscles to adjust your hand accordingly. Joint angles are optimised, contact forces are

tuned, and movement speeds are adjusted as necessary. All this happens without much conscious thought.

Now, imagine you are designing a prosthetic hand so that an amputee might manipulate this magazine in the same way. How do you make the hand respond naturally to the amputee's movement intentions and to unanticipated events, such as a sudden breeze that catches the page? For this task and others – hammering a nail, holding a coffee cup, feeding a child – prosthetic hands are expected to behave intuitively and reliably. But they do not yet meet these expectations, despite intensive research interest by engineers, clinicians and roboticists.

The hand is a complex thing to replicate. For one thing, it is highly articulated: the wrist can move in six different ways, the thumb in five, and each finger in four – giving a total of 27 degrees of freedom (DOF).<sup>2</sup> (Note that in this article we discuss DOF in the mechanical sense, i.e. an independent axis of movement – either rotation or translation – and not in the statistical sense, as would pertain to the number of values in a calculation.) But the limiting factor in prosthetic technology is not hardware: even do-it-yourselfers are able to 3D print a highly mechanised hand with many degrees of freedom. The problem is noisy, uncertain data – and this is a problem statisticians can help manage.

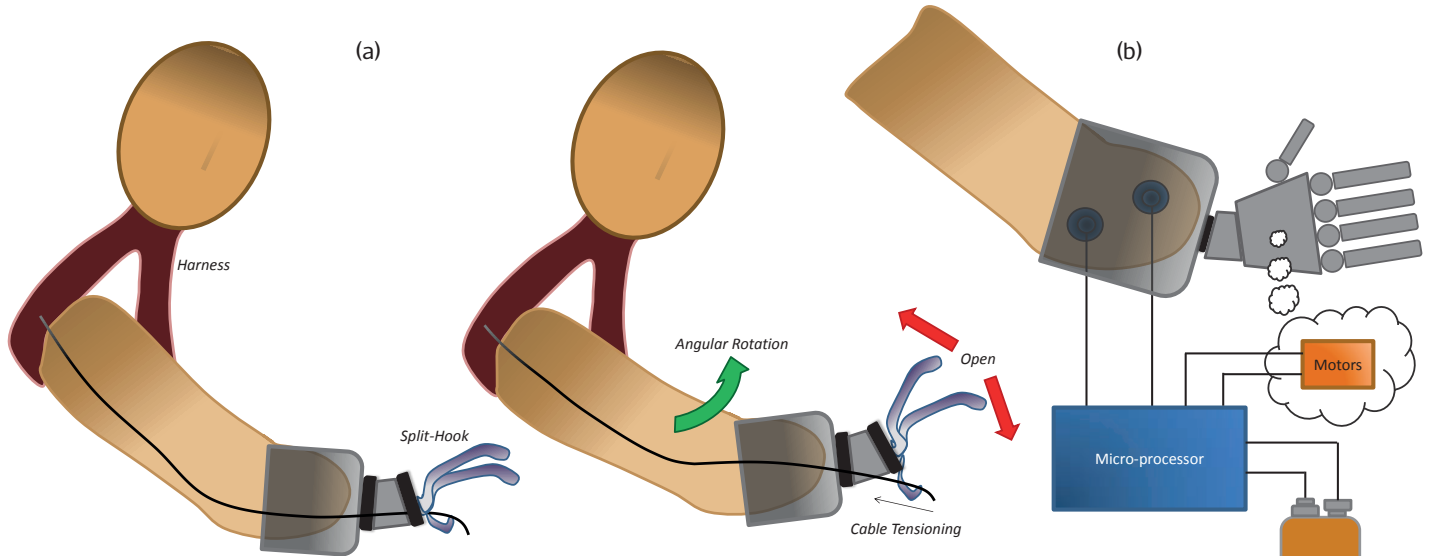
### Passive and active

Historically, upper-limb prostheses have had little need for data or statistical methods in order to function. They have been “passive” devices, which move according to cues provided by the amputee making use of other aspects of their anatomy. Figure 1(a), on page 32, shows an example. Here, the passive device features a harness system around both shoulders, linked to a 1-DOF hook; a cable wire pulls the hook open when the tension is increased (by spreading the shoulders apart) and the hook closes when the tension is relaxed (by bringing the shoulders back together).

By contrast, so-called “active” prostheses do rely on data. They combine sophisticated sensors with microprocessor technology and battery-powered actuators to coordinate flexion of one or more joints in the hand. Most active prostheses use electromyography (EMG) to detect when a muscle signal is generated.<sup>3</sup> This signal is then routed as a control signal to a motor to change the posture of the prosthetic hand, as in Figure 1(b), also on page 32.

Active devices are an exciting prospect, but they are expensive – selling for \$30 000–\$50 000 – and while they are mechanically capable of supporting many more DOFs than a traditional passive device, they do so typically only through pre-programmed schemes that intentionally limit the device to what it can reliably detect and control, which is usually one or two DOFs at a time. Rapid, reliable and simultaneous manipulation of multiple DOFs is not yet possible, and the primary roadblock is the decoding of movement intentions. An imperfect sensor in a challenging detection environment yields an erratic signal, which makes it hard to predict the action a user wants to perform. Uncertainty arises at multiple junctures. ▶

**LEFT** The RIC arm – a powered upper-limb prosthesis – and the hands that helped build it.<sup>1</sup> Photo courtesy of the Center for Bionic Medicine at the Shirley Ryan AbilityLab.



**FIGURE 1** (a) Passive body-powered prosthesis, activated to open a 1-DOF device. (b) Active prosthesis with multi-DOF hand containing motors for powered joint movement; the motors receive signals from sensors via a microprocessor unit.

## ► Signal detection

The first source of uncertainty concerns EMG detection. As was stated earlier, active prosthetic devices often rely on EMG sensors to detect the small electrical signals that are generated when muscles contract, and measuring EMG involves the placement of electrode pairs on the skin of the limb that remains after amputation. The signal from an EMG sensor pair reflects the changes in voltage in the muscle belly that occur as a result of muscle fibre recruitment in response to neural commands from the brain to the peripheral nerves (Figure 2). But accurately reading changes in voltage in a muscle is no easy task.

The muscle belly lies beneath layers of skin, fat and fascia, and bathes in a solution of blood, water and interstitial fluid, all of which can muffle the signal. Also, note that the muscle belly is a three-dimensional entity, wherein muscle fibres may be near or far from the electrodes on the skin surface. It is therefore possible that small-amplitude changes observed at the muscle fibre may be drowned out by high-amplitude signals generated by nearby nerves responding to unrelated physiological activity.

Furthermore, because the human neuromotor system has evolved with multiple anatomical redundancies (allowing the same movement to be performed through any number of nerve-muscle combinations), muscle fibre recruitment is an inherently stochastic process. Thus, it is difficult to directly link muscle activity to a specific desired action.

## Physiological change

EMG detection is further complicated by the physiological change that can occur within the residual limb. In the first 12 months post-amputation, limb volume can fluctuate 10% or more. But change can be seen in mature amputations as well, particularly in older patients, patients with oedema (a build-up of fluid under the skin), and patients with poor coupling between the prosthesis and their residual limb.<sup>4</sup>

Sweat can also introduce a source of noise as it drenches the EMG electrodes in water and ions, radically altering the arm's electro-conductive properties and thus the nature of the EMG signal (see Figure 3, and "Prosthetic signal and temperature", page 35). This problem can be difficult to avoid for two reasons: first, most prosthetic sockets are closed systems that trap warm air, and second, residual limbs typically do not shunt blood well, so heat stays localised to the residual limb. (This is all the more so for patients whose limb loss is due to diseases involving the circulatory system, such as diabetes and peripheral artery disease.)

## A moving target

The act of changing the position of the arm – when reaching for an object, say – creates additional detection problems. As the patient moves, the residual limb moves within the prosthesis socket, and the shifting of the socket interface creates a dynamic perturbation to the signal, which depends on limb position.

Consider a limb in an anatomically neutral (resting) position, where the socket has minimal load: any signal measured at the sensors can reasonably be assumed to pertain to intentional user control. Next, consider an alternative scenario where the user raises their arm, resulting in a gravitational load on the socket. This will bring some sensors into closer contact with the skin, and some sensors into weaker contact: now an intentional control signal will be amplified in some sensors and dampened in others. Consider a further case where the user holds a heavy object: now the socket is loaded in unpredictable ways, which cannot reasonably be accounted for in even the most thorough calibration protocols (see Figure 4, page 34).

## Basically Bayes

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## In the presence of all this noisy, uncertain data, one promising approach to decoding movement intentions is the use of Bayesian inference

control is the use of Bayesian inference, which is a method for updating the *prior* probability of a hypothesis with new information to create a *posterior* probability. The posterior probability then becomes the new prior as further information becomes available for updating. This updating of probabilities is achieved through Bayes' rule:

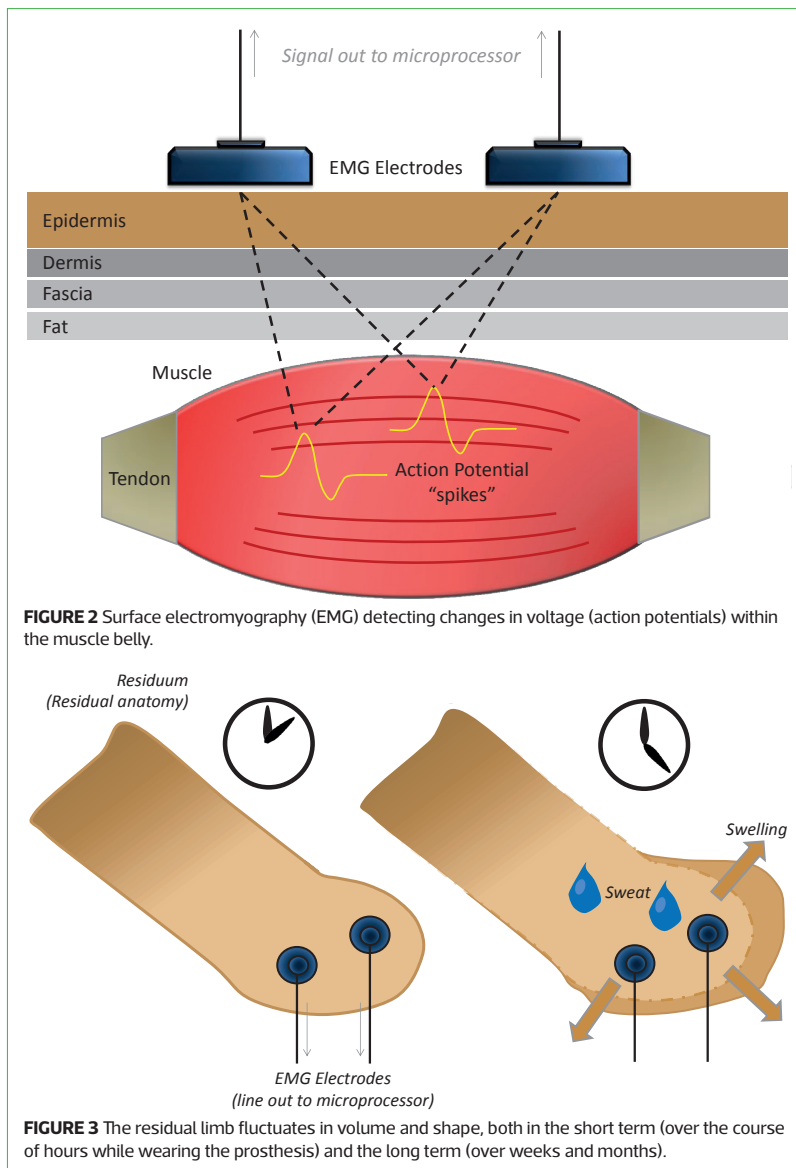
$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Bayesian methods emphasise the modelling of uncertainty. In the context of prosthetic control, we are interested in answering the question, "What is the probability that the patient intends to make a certain hand posture (*volition*), given that a certain *signal* is detected?" When the posterior probability reaches a threshold, we will want to send a *control* instruction to change the *state* of the hand. (See "Glossary" for definitions of italicised words.) As a general framework, the sensors will continually monitor the muscles of the intact anatomy; when a threshold signal is detected, the current state will be considered as part of the prior probability. Then the posterior probability will become the new prior as the next parcel of signal information streams in from the sensors.

Consider an example: a simple, two-sensor set-up, where an EMG sensor is situated over a muscle belly and counts the number of muscle spikes per second (a spike being an action potential; see Figure 2). It is common to define a signal threshold, so suppose we consider any signal with less than 10 spikes per second to be a "low" signal, and any signal with 10 or more spikes per second to be a "high" signal. The patient's prosthesis is currently in a fully closed state, but then the signal from the EMG sensors breaches a detection rate threshold, entering "high" territory. Does the patient want their hand to open, or not?

Suppose that, based on extended observations, this particular patient tends to want to open their hand approximately 20% of the time, and is content to leave their hand closed 80% of the time. This information gives the probabilities  $P(\text{Open}) = 0.20$  and  $P(\text{Closed}) = 0.80$ .

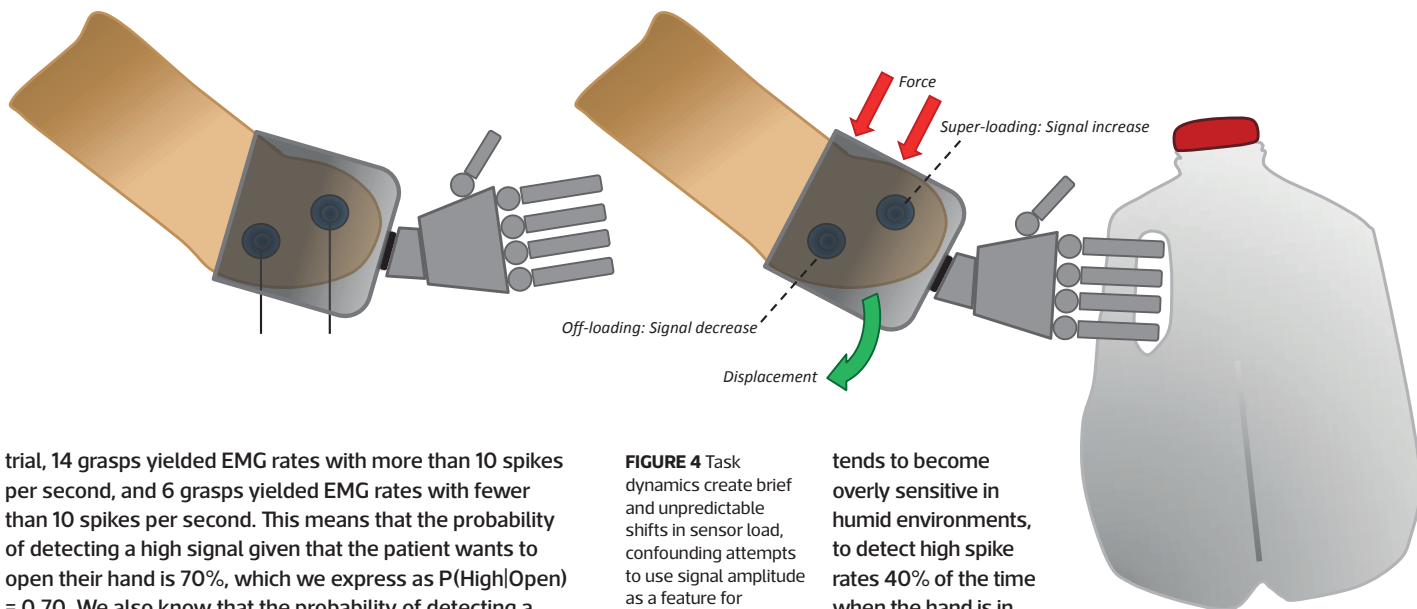
Now consider that the patient recently performed a calibration trial where she attempted 20 grasps (simple opening of the hand from a closed position). In the calibration



### Glossary: Prosthesis control

Control of a prosthetic device requires constant monitoring of the patient's body and reconfiguration of the prosthesis to match patient volition. Some useful terms are as follows:

- **State:** arrangement/activity of prosthesis (e.g. prosthesis finger angles)
- **Status:** arrangement/activity of intact anatomy (e.g. activity of finger flexor and extensor muscles)
- **Signal:** measurement of status (e.g. EMG signals measured from finger flexor and extensor muscles)
- **Volition:** intent to change state (e.g. desire to close the fingers into a grasp posture)
- **Control:** specification of effector state (e.g. turn on motors controlling prosthesis finger joints)
- **Degrees:** number of variables in a state.



**FIGURE 4** Task dynamics create brief and unpredictable shifts in sensor load, confounding attempts to use signal amplitude as a feature for prosthetic control.

tends to become overly sensitive in humid environments, to detect high spike rates 40% of the time when the hand is in a resting closed state. Increasing  $P(\text{High}|\text{Closed})$  to 0.4 changes our final posterior probability of  $P(\text{Open}|\text{High})$  from 0.988 to 0.572. In the dry condition, we reached 99% posterior probability in just three samples; in the moist condition, we would need 11 samples to reach the same threshold.

► trial, 14 grasps yielded EMG rates with more than 10 spikes per second, and 6 grasps yielded EMG rates with fewer than 10 spikes per second. This means that the probability of detecting a high signal given that the patient wants to open their hand is 70%, which we express as  $P(\text{High}|\text{Open}) = 0.70$ . We also know that the probability of detecting a low signal given that the patient wants to open their hand is 30%, written as  $P(\text{Low}|\text{Open}) = 0.30$ . When the hand was resting in a closed state during the calibration period, a low spike rate occurred 90% of the time (and thus the closed hand yields a high spike rate only 10% of the time, so  $P(\text{High}|\text{Closed}) = 0.10$ ).

Given that we are now encountering a high spike rate in our hypothetical example, we can use Bayes' rule to calculate the probability that the patient wants to open their hand as follows:

$$\begin{aligned}
 &P(\text{Open}|\text{High}) \\
 &= \frac{P(\text{High}|\text{Open})P(\text{Open})}{P(\text{High}|\text{Open})P(\text{Open}) + P(\text{High}|\text{Closed})P(\text{Closed})} \\
 &= \frac{0.70 \times 0.20}{(0.70 \times 0.20) + (0.10 \times 0.80)} \\
 &= 0.636
 \end{aligned}$$

This posterior probability can inform the new prior probability, as we now have a 63.6% expectation that the hand is intended to be open at this time, so  $P(\text{Open}) = 0.636$  and  $P(\text{Closed}) = 0.364$ . If, in the next interval, the signal is still in the high range, the probability that the patient wants to open their hand is now:

$$\begin{aligned}
 &= \frac{0.70 \times 0.636}{(0.70 \times 0.636) + (0.10 \times 0.364)} \\
 &= 0.925
 \end{aligned}$$

Updating the probabilities one more time after a third high spike rate, we get  $P(\text{Open}|\text{High}) = 0.988$ . By now, we are reasonably confident that the patient wants to open their hand. But here is where confounders can compromise our prediction. Suppose a moisture detector in the socket senses excessive humidity (sweat). We may reasonably expect EMG, which

### Precedent and paths forward

Why use Bayesian inference? Is it possible to obtain reasonable results using frequentist methods? While a full treatment of these classic questions is beyond the scope of this article, there is ample evidence that frequentist approaches are not dissimilar from Bayesian approaches in their delivery of results. However, there are good reasons to choose the latter over the former in this scenario.

One common concern of a Bayesian approach is that of an uninformative prior. But in prosthetic prediction tasks the prior is defined through calibration exercises. These are fairly reliable because they are straightforward and designed to reflect the actual usage scenario. In addition, a Bayesian approach is more suited to the integration of multiple distributions simultaneously, such as the tandem sources of uncertainty from the EMG sensor and the humidity sensor. For amputees, the sources of uncertainty are many and substantial, making Bayesian methods especially useful.<sup>5</sup>

Bayesian inference is also familiar to the community of physiological researchers as Bayesian architectures have been successfully used to describe sensorimotor adaptation models in able-bodied humans. In these models, the brain coordinates quick movements by continually predicting the outcome of movement commands; relying entirely on sensory feedback would be too slow and create delays. The brain makes movement predictions by using prior knowledge of the dynamics of the body and the environment. The brain then updates the movement prediction with the delayed sensory

feedback. How much should the brain rely on the movement prediction rather than the sensory feedback? According to Bayesian models, the combination depends on the uncertainty of each source of information. Both the movement prediction and the sensory feedback are estimated with some uncertainty, caused by noisy motor commands, imprecise sensors, environment changes and many other factors – but the brain relies more heavily on the information with less uncertainty. For example, if you are moving in the dark (where sensory feedback has high uncertainty), you will rely more heavily on your movement predictions (the prior knowledge of how your body moves and what is in the room around you).

These foundational works in the human motor system provide key insight into prosthetic control for amputees. The current state of the art is categorical prediction of volition, in which an algorithm is designed to classify signals as pertaining to one of a small number of pre-programmed grasp types.<sup>6</sup> Once a volition is detected with confidence above a specified threshold, that particular grasp posture is generated via control signals to the hand's motors and fixed for a specified time (typically 1 second); for this interval, no signals from the sensors are needed because the grasp is executed pro forma. However, the target for next-generation prostheses is to maintain a continuous – and continually updating – posture. This requires the monitoring of signals at all times, adjusting the hand motors accordingly. There are critical limitations to this approach, including the need to extend prosthesis battery life and the need for constant attention to the device. But, from the standpoint of the human-machine interface, the continuous measurement of uncertainty and adaptation to change would make the most naturalistic experience.

For active prostheses, new sensing paradigms may help reduce the uncertainty in measurement. For example, force myography (FMG) detects patient volition through volume



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## Approaches based in artificial intelligence are extending the possibilities of intuitive prosthetic control

changes in the muscle, rather than the volatile electrical signals that sometimes do and sometimes do not indicate an actual volition. And because FMG is based on measurement of the structural dynamics of the muscle belly, rather than detection of the sub-surface electrical activity, patient sweat is not a concern. Thus, FMG presents two opportunities to reduce the denominator term equivalent to P(High|Closed): less baseline noise, and no risk of increased sensitivity.

Additionally, approaches based in artificial intelligence are extending the possibilities of intuitive prosthetic control via their array of pattern recognition strategies. An emergent trend in prosthetic technology is shared control, where the hand's posture is controlled along a spectrum, with some portion of the control signal reflecting the patient's status as measured through sensors and the remainder reflecting algorithmic decision-making performed autonomously within the processor.

These and other paths forward present promising opportunities, and perhaps one day prosthetic hands will meet the expectations set for them: to behave intuitively and reliably. When that time comes, a future prosthesis user may find themselves in a situation similar to the one you are in now: reading the concluding sentence of a magazine article while their hand gently curls the corner of the page, ready to turn over and continue with its ongoing choreography of postures. ■

### Prosthetic signal and temperature

Enclosed body parts generate heat, which leads to sweat, which confounds electrically based sensors at the skin's surface: sweat contains water and electrically charged particles (ions), which will alter an EMG signal. Separately, beneath the skin's surface, heat changes conductivity of these ions at the level of the cell membrane, occurring both in neurons and muscle fibres. The relationship between the ion conductivity and these membranes is given by the Nernst equation,

$$V = \frac{R \cdot T}{F} \ln \frac{\chi_{\text{out}}}{\chi_{\text{in}}}$$

where  $R$  and  $F$  are respectively the universal gas constant ( $8.3 \text{ J K}^{-1} \text{ mol}^{-1}$ ) and Faraday's constant ( $9.6 \times 10^4 \text{ C mol}^{-1}$ ),  $\chi$  is the concentration of an ion inside or outside the cell, and  $V$  is the resting potential difference (volts) across the cell membrane. If internal body temperature ( $T$ ) rises due to poor heat shunting, the conductive properties of the neuron and muscle will change, altering the EMG signal at the surface of the skin.

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