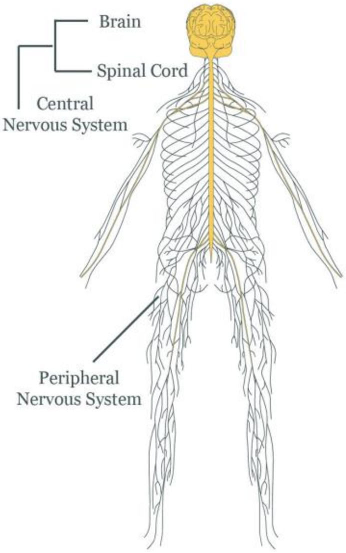
Biological Information: Neuroscience

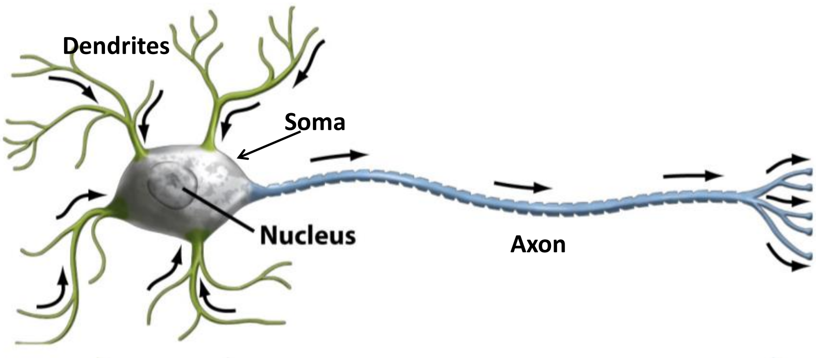
The Nervous System

- Sensory neurons
- Motor neurons
- Interneurons

Gathers, stores, process, and communicate vast amounts of information and uses it successfully.



Neuron



Neuron: Information Flow

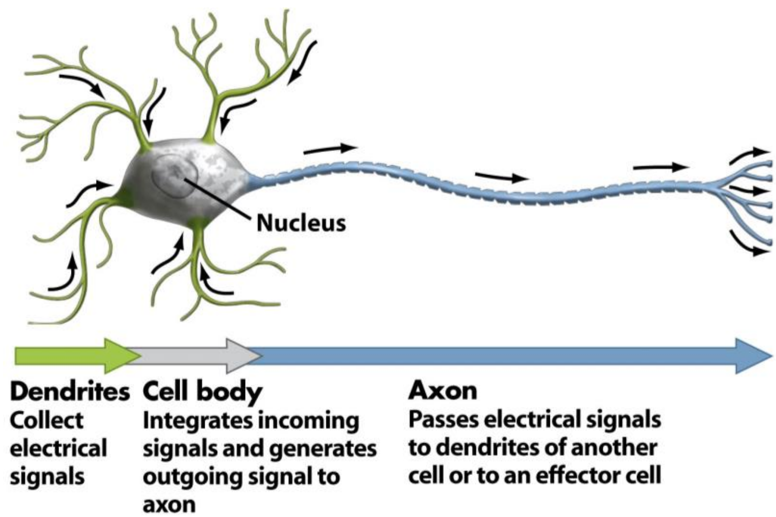


Figure 45-2b Biological Science, 2/e

Action Potential (or Spikes)

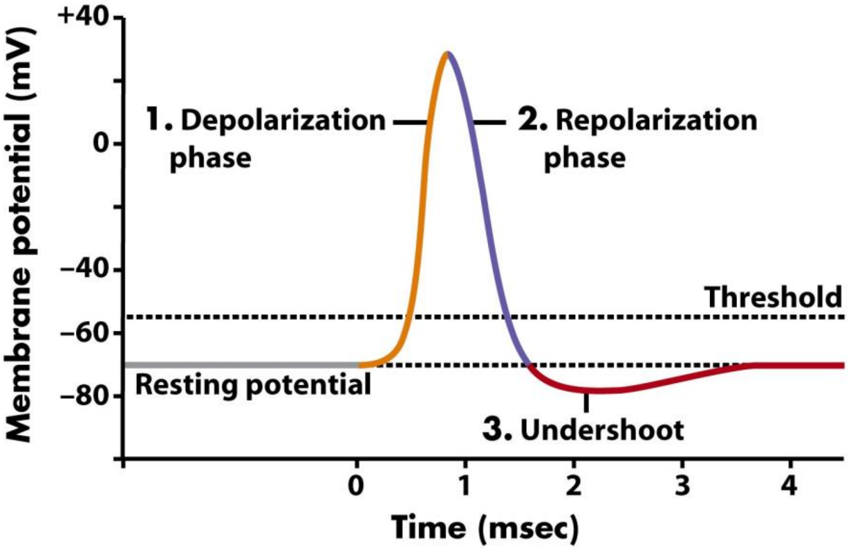
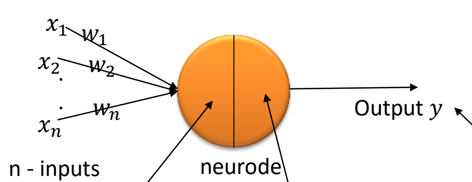
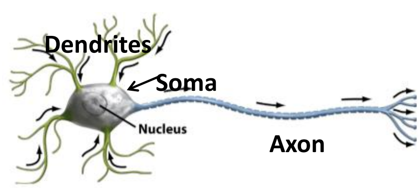


Figure 45-5 Biological Science, 2/e

Sidebar: Neural Networks





Transfer Function

$$I = \sum_{j=1}^{n} w_i x_i$$

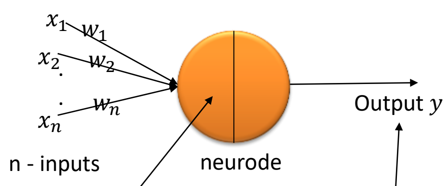
Activation Function

$$f(I) = \frac{1}{1 + e^{I}}$$

Output Function

$$y = \begin{cases} f(I), & if\ f(I) > T \\ 0, & otherwise \end{cases}$$

Neural Networks: The Perceptron



The Perceptron Training Algorithm
For each pattern in training set
  apply next pattern to perceptron
  record output, y
  apply learning rule (change weights)

Transfer Function

$$I = \sum_{j=1}^{n} w_i x_i$$

Output Function

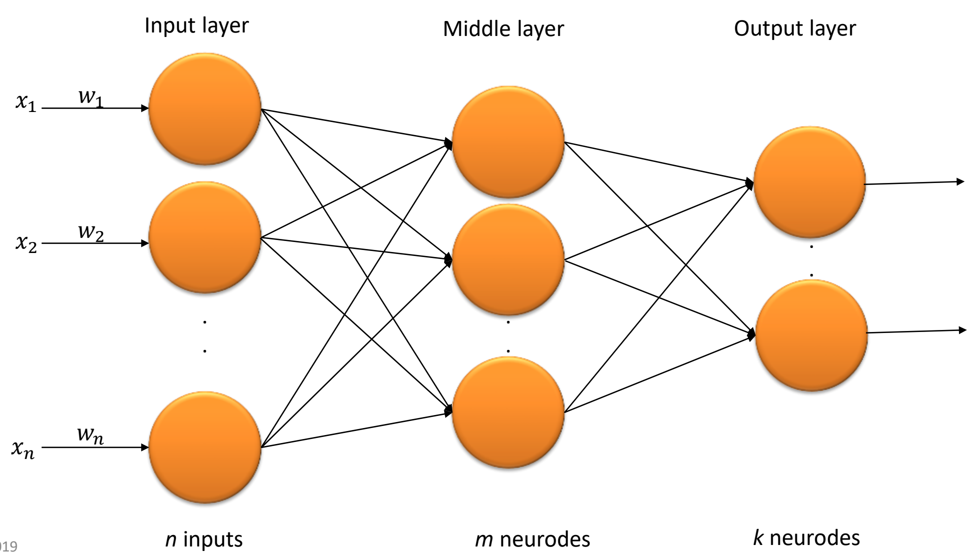
$$y = \begin{cases} +1, & \text{if } f(I) > T \\ -1, & \text{otherwise} \end{cases}$$

Learning Rule

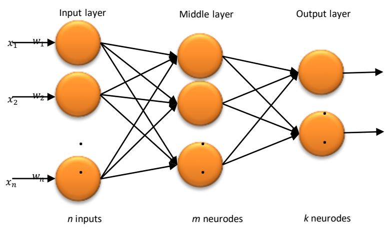
$$\boldsymbol{w}_{new} = \boldsymbol{w}_{old} + \beta y \mathbf{x}$$

$$\beta = \begin{cases} +1, & \text{if perceptron's answer is correct} \\ -1, & \text{if perceptron's answer is wrong} \end{cases}$$

Neural Networks: Backpropagation Networks



Neural Networks: Backpropagation Networks



Forward Activity

$$I = \sum_{j=1}^{n} w_i x_i$$

$$f(I) = \frac{1}{1+e^{I}}$$

Backpropagation

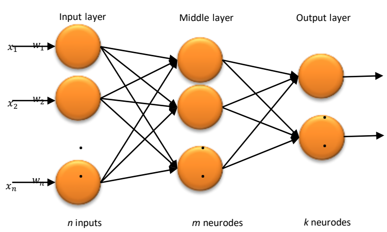
$$\Delta w_{ij} = \beta \, E \, f(I)$$

$$E_j^{output} = y_j^{desired} - y_j^{actual}$$

$$E_i^{middle} = \frac{df(I_i^{middle})}{dI} \sum_{j=1}^{n} (w_{ij} E_j^{output})$$

Backpropagation Algorithm
set maximum acceptable error
repeat
  total error = 0
  for each pattern in training set **do**
    for each neurode in the middle layer **do**
      compute I_i
      compute $f(I_i)$
    for each neurode in the middle layer **do**
      compute output y_i
    for each neurode in the output layer **do**
      compute Error E_i
      total error = total error + E_i
    for each neurode in the middle layer **do**
      backpropagate output layer error to middle
    for each neurode in the input layer **do**
      backpropagate middle layer weight change
until (total error < maximum acceptable error

Neural Networks: Backpropagation Networks



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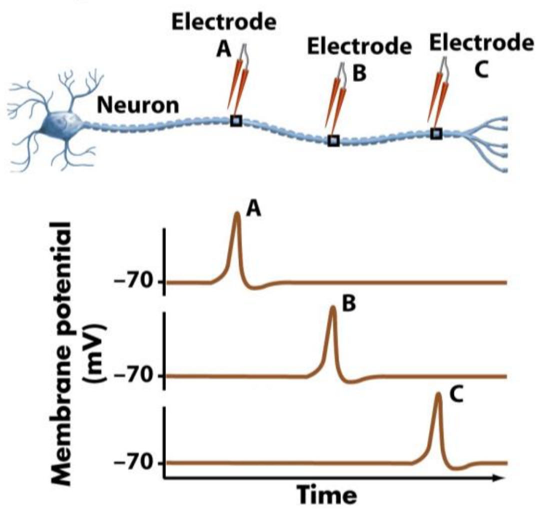
Supervised Learning

Action Potential (or Spikes)



Perception: "Raw Data"

- Perception of the world is constructed out of the raw data sent to the brain by sensory nerves.
- All raw data arrives in the form of sequences of identical voltage pulses (action potentials or **spikes**)
- Spike sequences are "language of the brain".

Neural Code

- **Neural Code:** Action potentials are the elementary units.
- **All-or-none law:** Individual sensory neurons respond to external stimuli by producing spikes, or not responding at all.

All-or-none Coding

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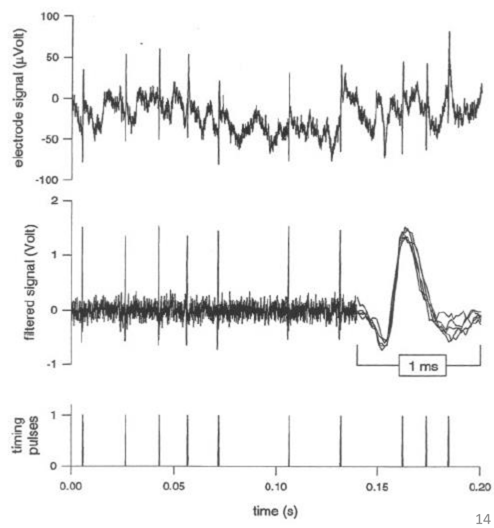
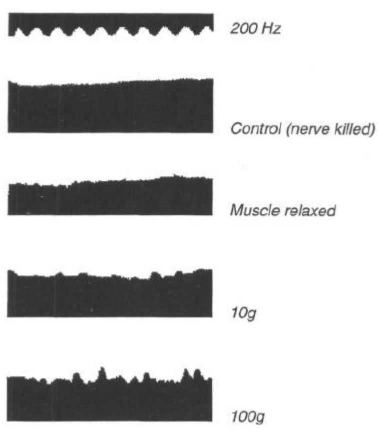


Firing Rate *vs* Stimulus

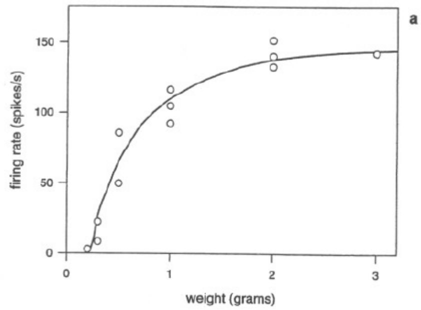
- In response to a static stimulus, such as a continuous load on a stretch receptor, the rate of spiking increases as the stimulus becomes larger.

  Rate Coding: The rate, or frequency of spikes indicates the intensity of the stimulus.

Firing Rate *vs Stimulus*



Rate Coding



- The rate of spiking increases as the stimulus becomes larger.

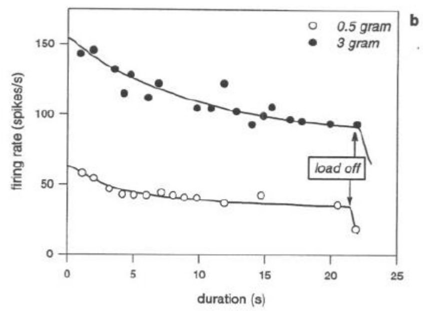
Firing Rate *vs* Stimulus

- In response to a static stimulus, such as a continuous load on a stretch receptor, the rate of spiking increases as the stimulus becomes larger.

  Rate Coding: The rate, or frequency of spikes indicates the intensity of the stimulus.

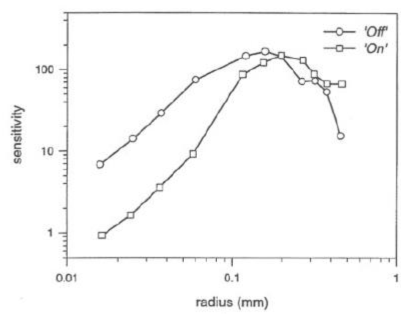
- If a stimulus is continued for a very long time, the spike rate begins to decline. This is called **adaptation**.

Adaptation



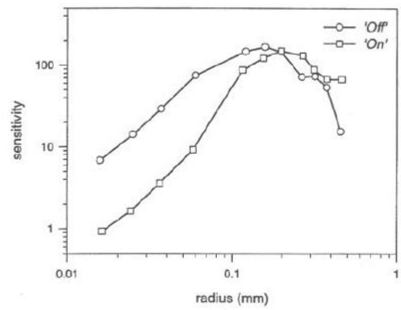
- Spike rate declines if the stimulus is continued for a long time.

Feature Selectivity



- Sensitivity of retinal ganglion cells in the frog as a function of the radius of the light stimulus. Increase in stimulus size increases sensitivity, but decreases when stimulus larger than 0.2 mm in radius.

Feature Selectivity



Bug detectors!

- Sensitivity of retinal ganglion cells in the frog as a function of the radius of the light stimulus. Increase in stimulus size increases sensitivity, but decreases when stimulus larger than 0.2 mm in radius.

Central Questions

- **The encoding problem:** What information does a spike train convey about the world?
- How to make sense of the pattern of spikes?
- **The decoding problem:** Can we recreate the continuous time dependent world that is encoded in discrete spike trains?

Understanding Neural Code

- Involves understanding the relationship between spike trains and real events in the sensory world.
- It is not a one-to-one mapping, unfortunately.
- Each sensory stimulus is assigned randomly to one of the possible spike trains.
- Probability Theory provides a possible medium.

A Probabilistic Model

- $s(t)$ represents a time-dependent stimulus
- $t_1, t_2, \ldots, t_N$ or $\{t_i\}$ represents arrival times of each spike
- $P[\{t_i\}|s(t)]$ is the conditional probability of spike train given the stimulus
- $P[s(t)]$ is the probability distribution of the signals (stimuli) [the ensemble of signals in the world]

A Probabilistic Model

- $P[\{t_i\}, s(t)]$ is the joint distribution of signals and spike trains. Where

$$P[\{t_i\}, s(t)] = P[\{t_i\}|s(t)] \times P[s(t)]$$

- What we want: based on an observation of a spike train $\{t_i\}$ can we say something about the stimulus $s(t)$?

- The spike train has been chosen at random from the distribution $P[\{t_i\}]$

A Probabilistic Model

- $P[\{t_i\}, s(t)]$ is the joint distribution of signals and spike trains. Where

$$P[\{t_i\}, s(t)] = P[\{t_i\}|s(t)] \times P[s(t)]$$

- The spike train has been chosen at random from the distribution $P[\{t_i\}]$

- $P[\{t_i\}, s(t)]$ is also the joint distribution of signals and spike trains. Where

$$P[\{t_i\}, s(t)] = P[s(t)|\{t_i\}] \times P[\{t_i\}]$$

- $P[s(t)|\{t_i\}]$ is the response-conditional ensemble

A Probabilistic Model

- $P[\{t_i\}, s(t)]$ is the joint distribution of signals and spike trains. Where

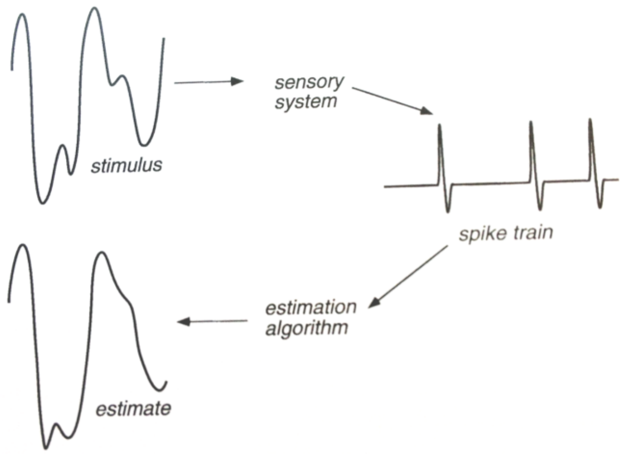
$$P[\{t_i\}, s(t)] = P[\{t_i\}|s(t)] \times P[s(t)] = P[s(t)|\{t_i\}] \times P[\{t_i\}]$$

$$\rightarrow P[s(t)|\{t_i\}] = P[\{t_i\}|s(t)] \times \frac{P[s(t)]}{P[\{t_i\}]}$$

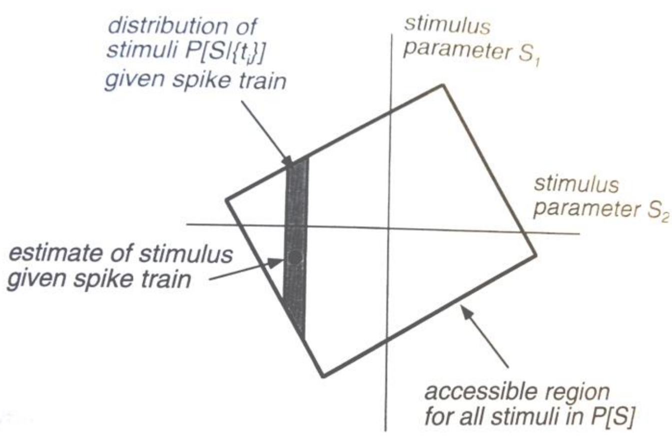
Timing Code

- Given a time-dependent stimulus $s(t)$ a complete probabilistic description of the neural response is contained in the conditional distribution $P[\{t_i\}|s(t)]$
- That is, relative likelihood that spikes will arrive at times $\{t_1, t_2, \ldots, t_N\}$
- The mean of $P[\{t_i\}|s(t)]$ is the time dependent firing rate, $r(t)$
- The probability of finding a spike at time, t is $p(t) = r(t)\Delta(\tau)$where $\Delta(\tau)$ is the window surrounding time, t

Stimulus Estimation



Stimulus Space



Information in Spike Trains

- (How) Can we quantify the information that sensory neurons convey about the world?
- Spike train entropy

$$H(spike\ train) = -\sum_n p(n) \log p(n)$$

- Where $p(n)$ is the probability of observing n spikes in a given window $\Delta\tau$, and $\sum_n p(n) = 1$
- What spike count distribution will maximize the spike count entropy? This is the maximum amount of information one can get from a spike train.

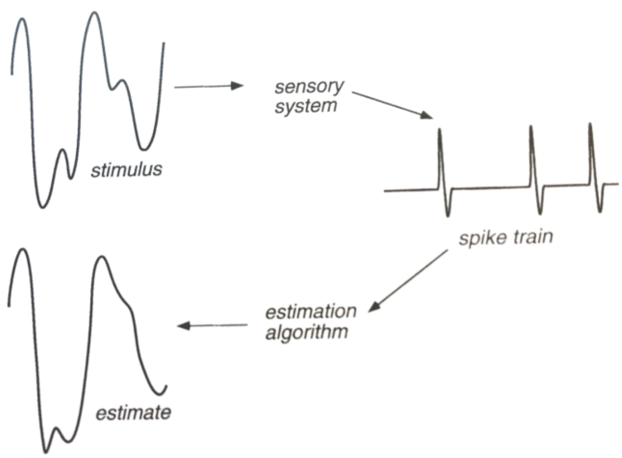
Information in Spike Trains

- Experiments in several systems demonstrate that real neurons and synapses approach limits to information transmission set by the spike train entropy.
- Sensory neurons pack as much information as is possible into spike trains sent to the brain.

The Big Puzzle

- How physical signals, transduced by the nervous system, give rise to high-level semantic information?
- Some miniscule parts of this are know, but largely it is still a mystery.

Stimulus Estimation



From Single Neurons to the Brain

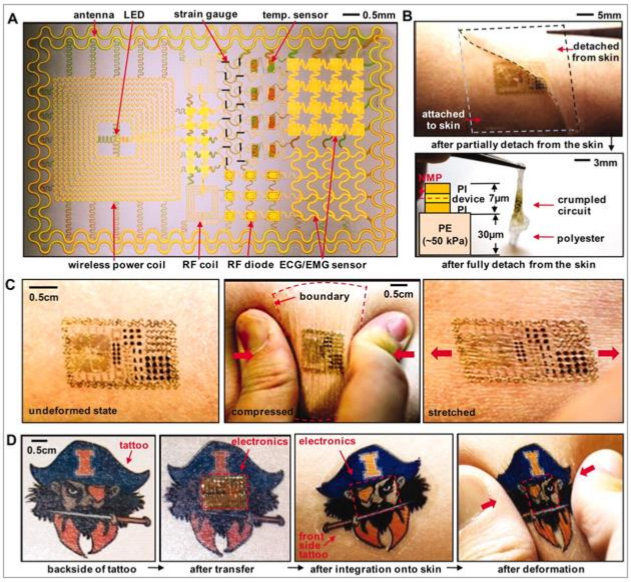
- fMRI (Functional Magnetic Resonance Imaging) measures brain activity (non-invasively) by measuring blood flow.
- Can be used to correlate perception or activity with patterns in the brain.

Reconstruction from Brain Activity

- Record brain activity while the subject watches several hours of movie trailers.
- Build dictionaries (i.e., regression models) that translate between the shapes, edges and motion in the movies and measured brain activity. A separate dictionary is constructed for each of several thousand points at which brain activity was measured.
- Record brain activity to a new set of movie trailers that will be used to test the quality of the dictionaries and reconstructions.
- Build a random library of ~18,000,000 seconds (5000 hours) of video downloaded at random from YouTube.
- Put each of these clips through the dictionaries to generate predictions of brain activity. Select the 100 clips whose predicted activity is most similar to the observed brain activity. Average these clips together. This is the reconstruction.

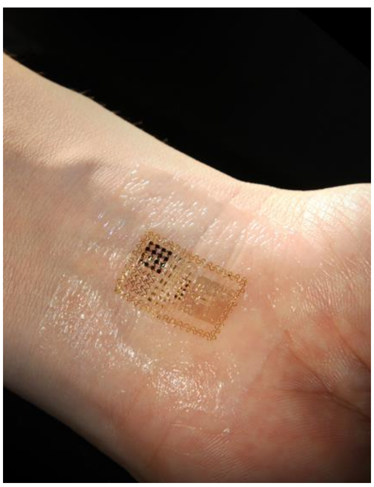
  Watch video.

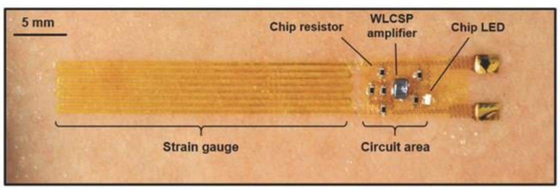
Flexible Stretchable Electronics

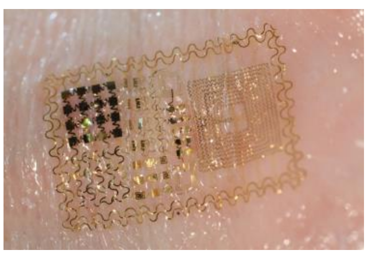


Dae-Hyeong Kim et al. Science 2011;333:838-843

Flexible Stretchable Electronics







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- Epidermal Electronics (Todd Coleman *et al*), Science 12, August 2011.