

Teoría de señales

SEÑALES ELECTROFISIOLÓGICAS

Señales

- Concepto:

Señales

- Concepto:
- *Las señales son magnitudes físicas o variables detectables mediante las que se pueden transmitir mensajes o información.*

Ejemplos de señales

- Voz
- Imágenes (fotografías, Rx, TAC, MRI, PET, volumétricas, microscopía confocal, video, etc)
- Ultrasonido
- Temperatura
- Radar
- Actividad geodésica
- Viento
- **Actividad eléctrica**

Naturaleza de las señales

Naturaleza de las señales

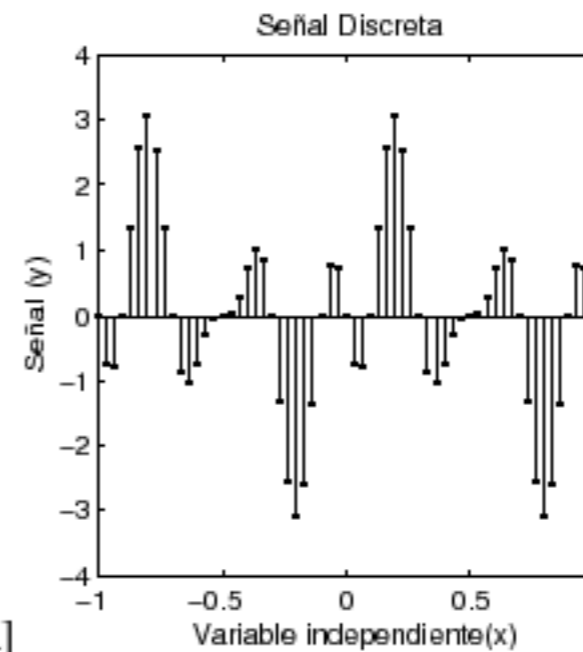
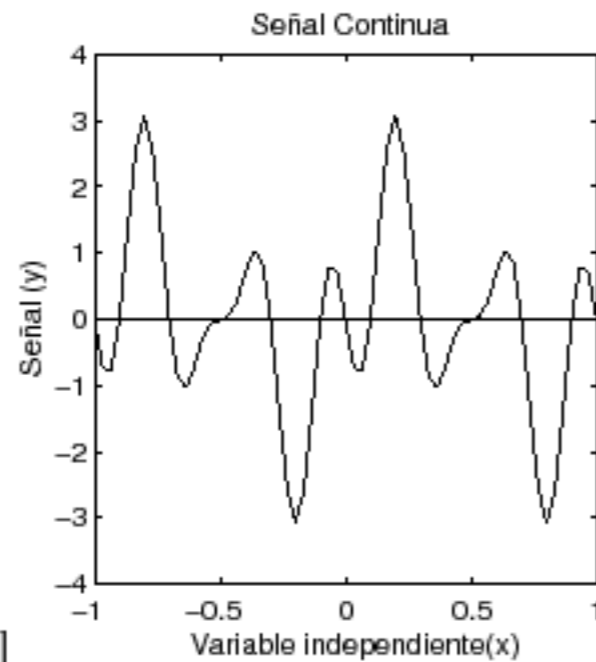
- Señales **continuas** (\sim analógicas) y señales **discretas** (\sim digitales)

Naturaleza de las señales

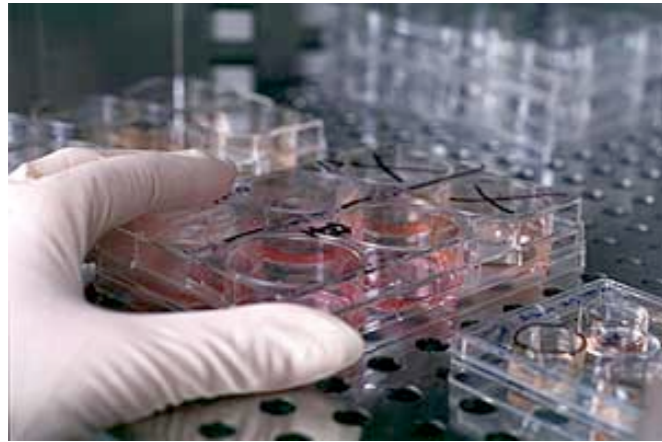
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Naturaleza de las señales

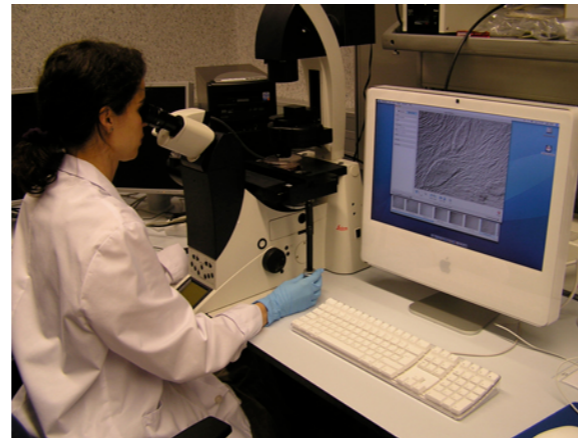
- Señales **continuas** (\sim analógicas) y señales **discretas** (\sim digitales)



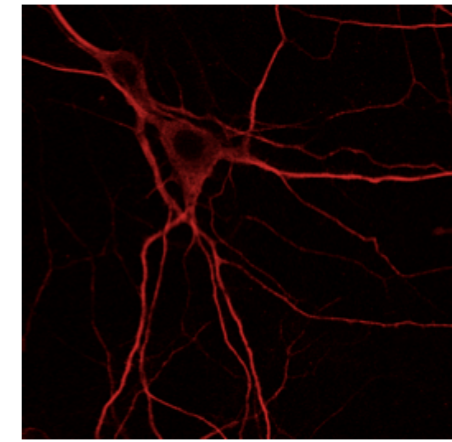
Señal en el mundo continuo



Discretización (muestreo)



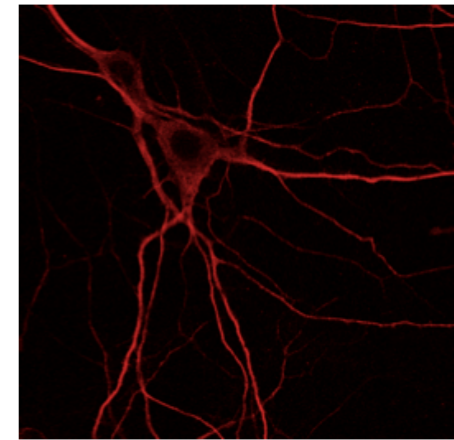
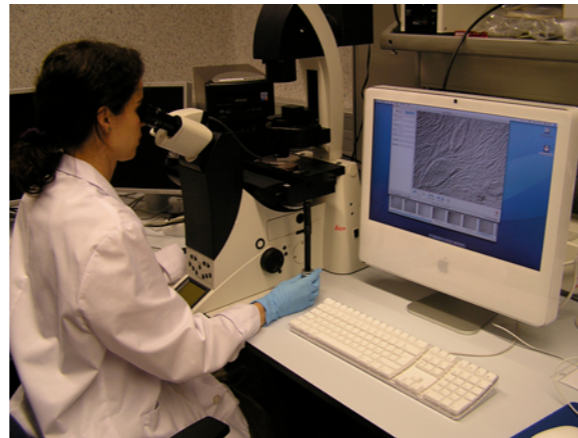
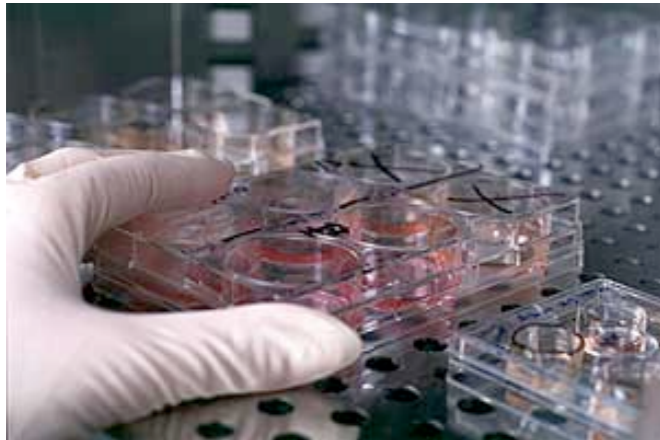
Señal en el mundo discreto



Señal en el mundo continuo

Discretización (muestreo)

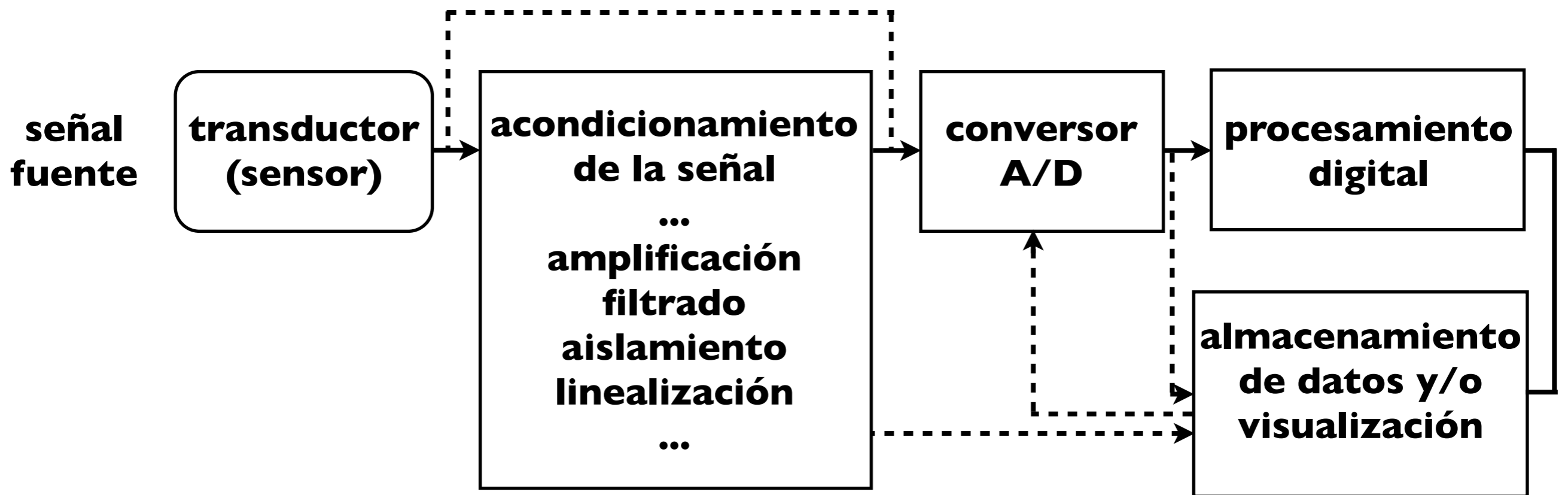
Señal en el mundo discreto



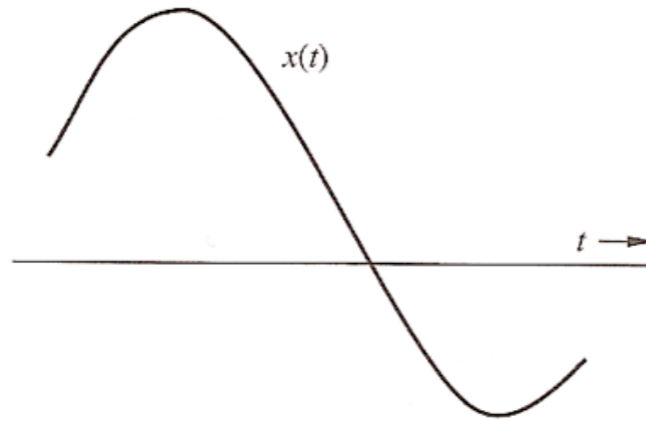
Transformación entre el mundo continuo y discreto

- Conversión Análogo-Digital (CAD)
- Teoría de muestreo

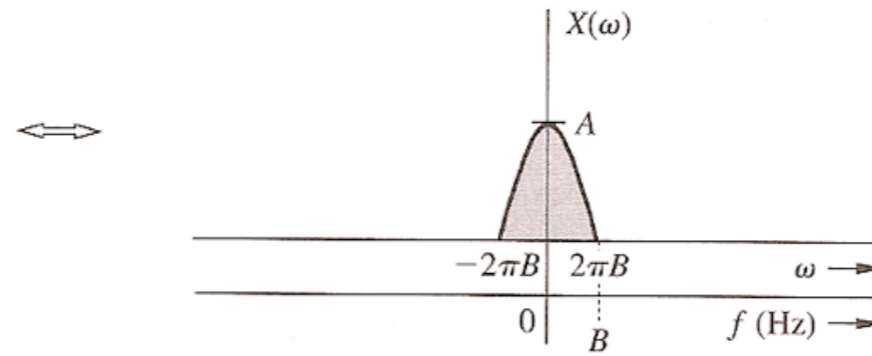
Adquisición, conversión A/D y almacenamiento



Conversión A/D



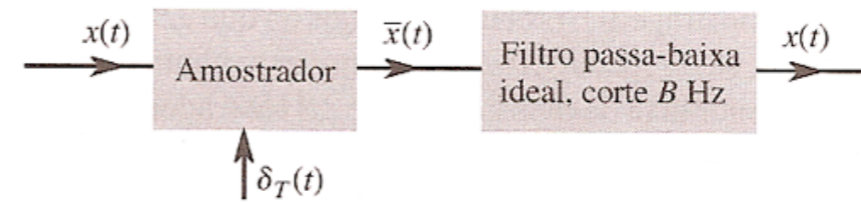
(a)



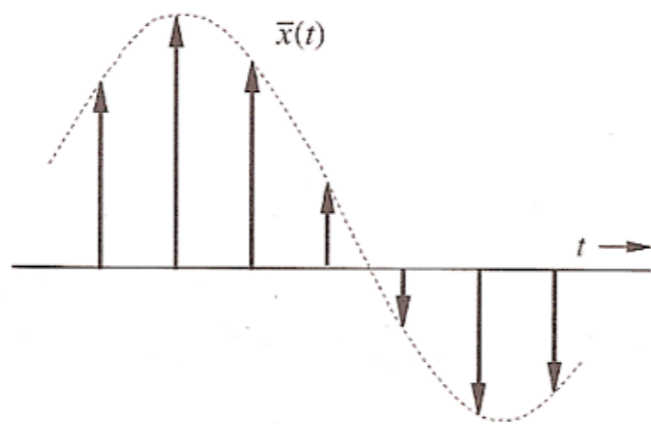
(b)



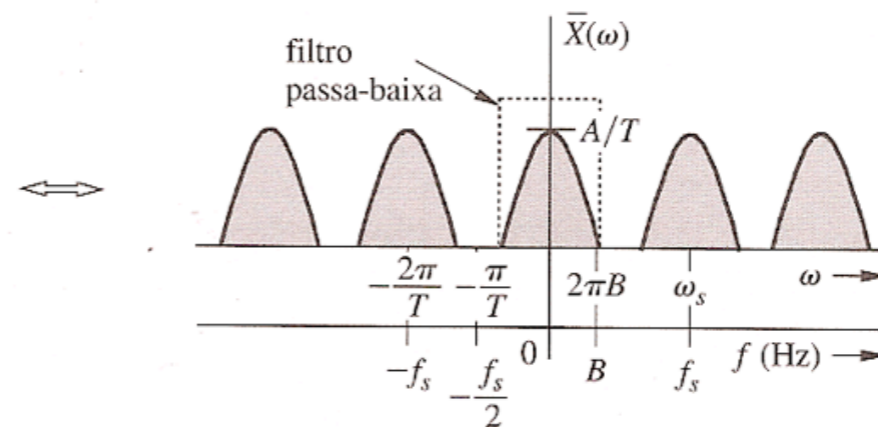
(c)



(d)



(e)



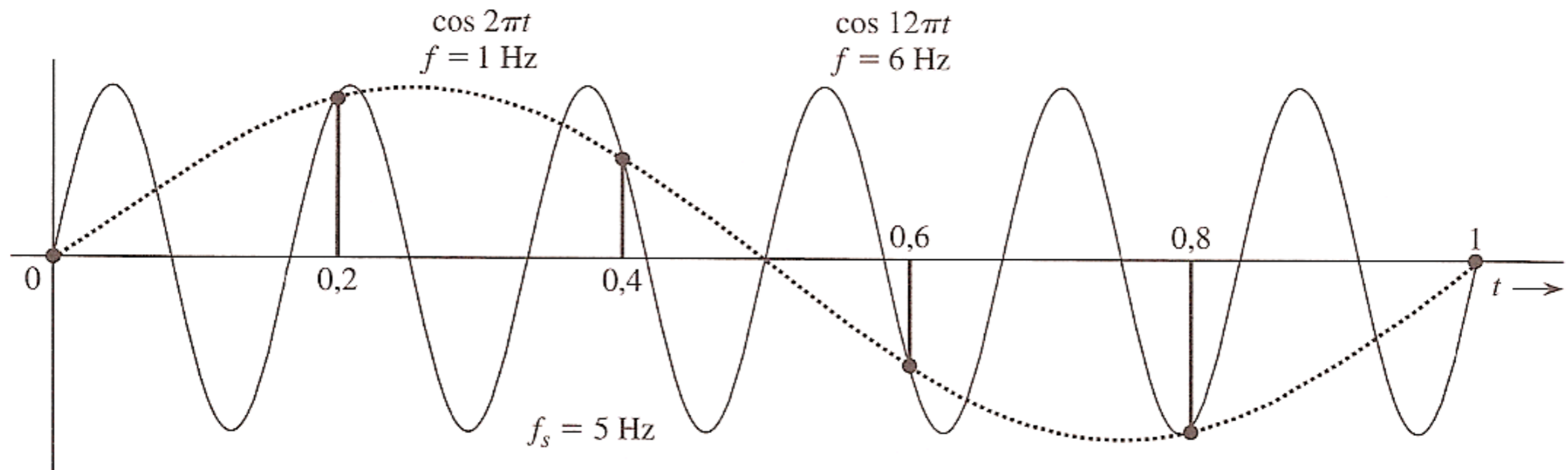
(f)

Teorema del muestreo

Nyquist

Una señal real cuyo espectro es limitado en banda a B Hz [$X(\omega) = 0$ para $|\omega| > 2\pi B$] puede ser reconstruido exactamente (sin ningún error) a partir de sus muestras tomadas uniformemente a una frecuencia de **$f_s > 2B$** muestras por segundo.

Error en el muestreo ($f_s < 2B$) 'aliasing'



Aliasing. Ejemplos

Imágenes

Video

Música

Muestreo
correcto



<http://www.academicearth.org/lectures/aliasing-demonstration-with-music>

Muestreo a
 $f_s < 2B$



helicóptero

Por lo tanto:

- para reconstruir $x(t)$ a partir de $x'(t)$, se debe cumplir que:

$$f_s > 2B$$

- como el intervalo de muestreo es $T = 1/f_s$,

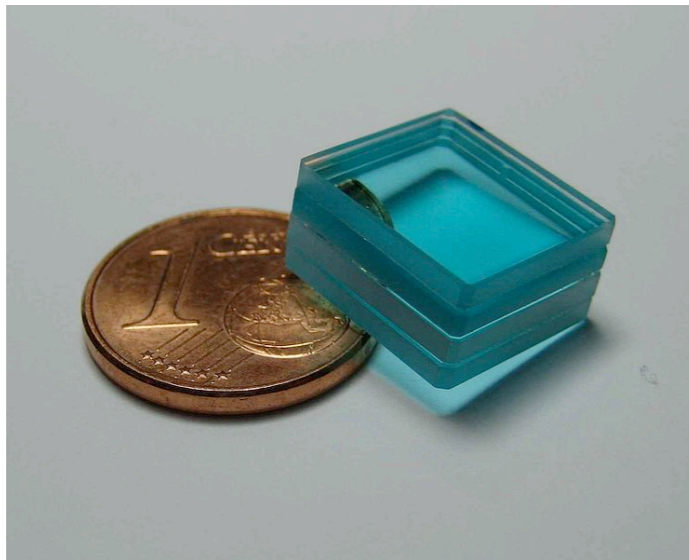
$$T < \frac{1}{2B}$$

Ojo:

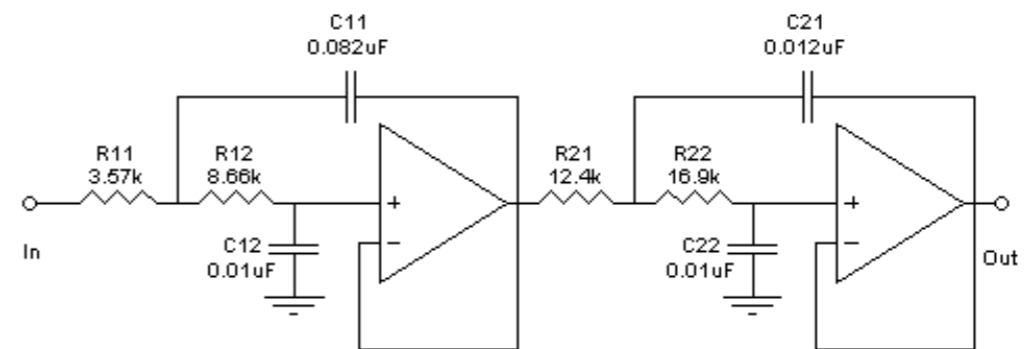
- Las señales reales tienen una duración finita y muchas veces su contenido en frecuencia no tiene un límite superior ... Se deben usar filtros de entrada 'antialiasing'

Ojo:

- Las señales reales tienen una duración finita y muchas veces su contenido en frecuencia no tiene un límite superior ... Se deben usar filtros de entrada 'antialiasing'



Filtro pasa-bajo de una cámara de video digital

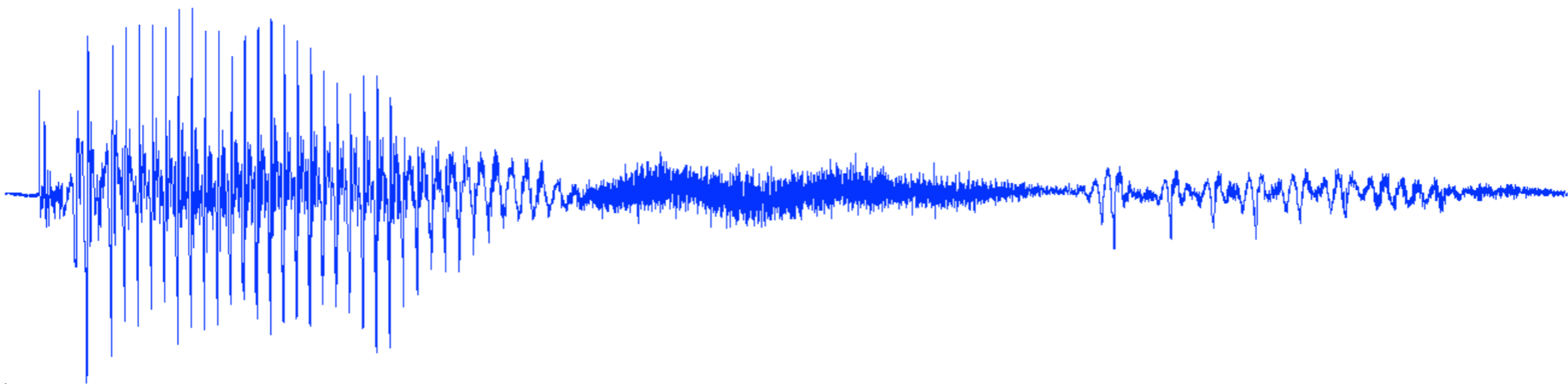


Filtro pasa-bajo analógico tipo Butterworth

Conversión entre el mundo continuo y discreto

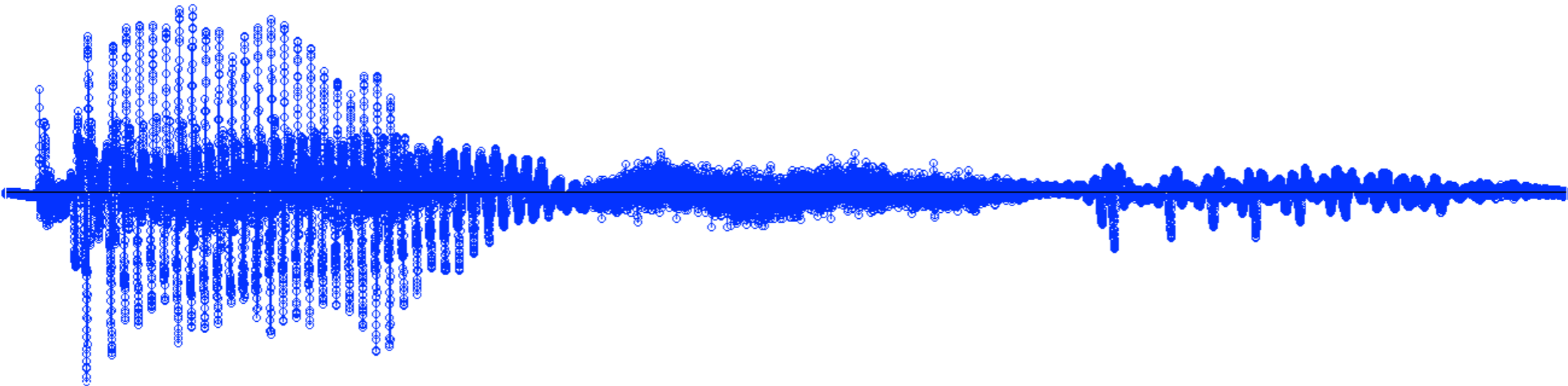
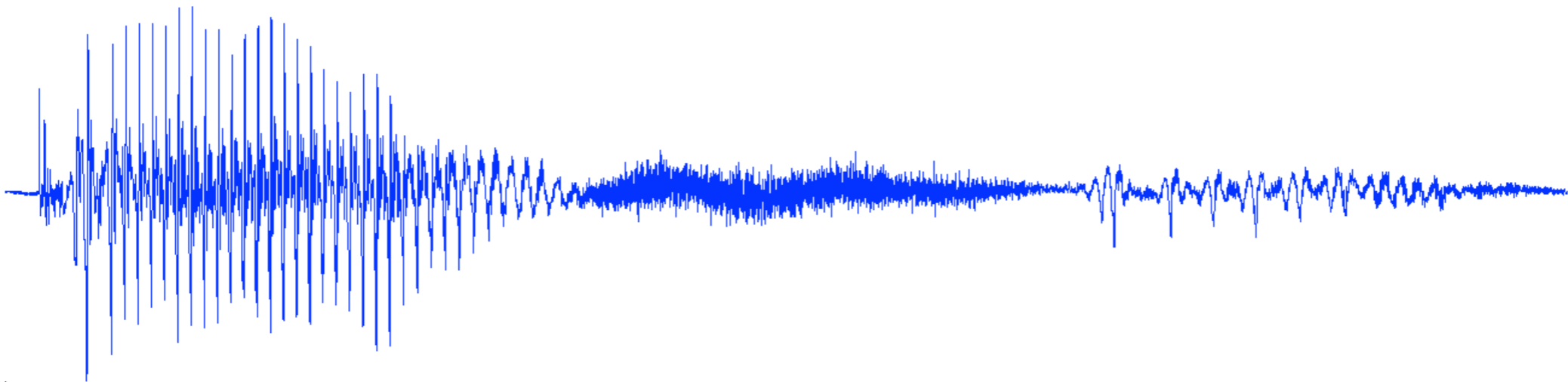
Conversión entre el mundo continuo y discreto

taza



Conversión entre el mundo continuo y discreto

taza

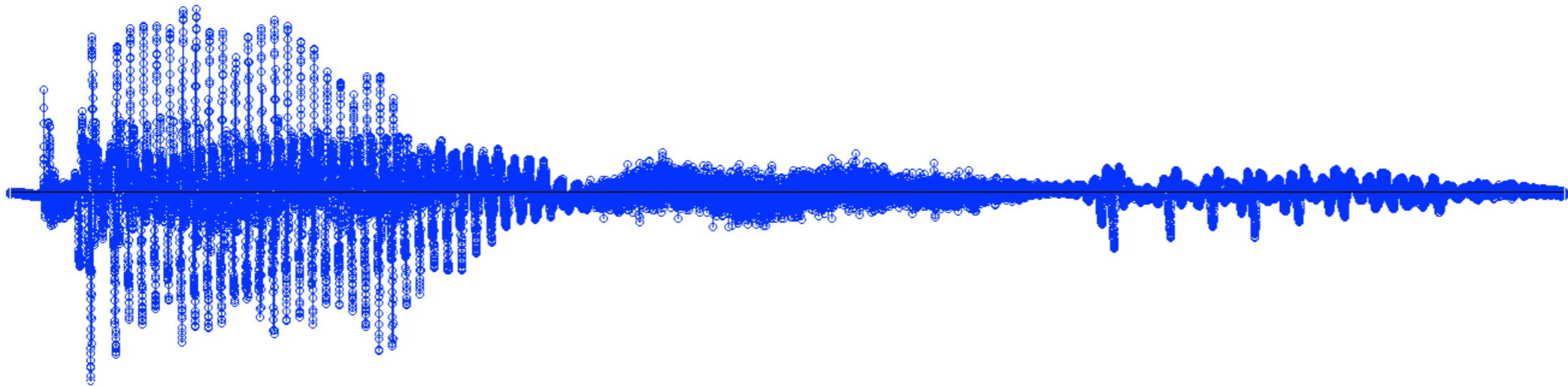


Propiedades de la conversión A/D

Frecuencia de muestreo

Propiedades de la conversión A/D

Frecuencia de muestreo



Cantidad de muestras que tomo por unidad de la variable independiente [tiempo, espacio, etc] (Hz, pixeles, etc.)

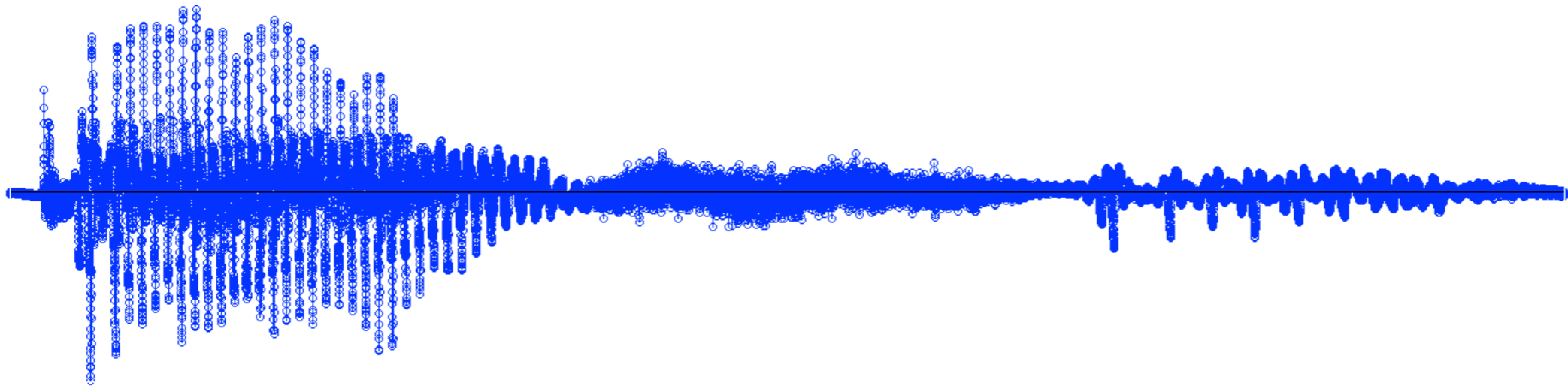
Teorema de Nyquist

Propiedades de la conversión A/D

Precisión

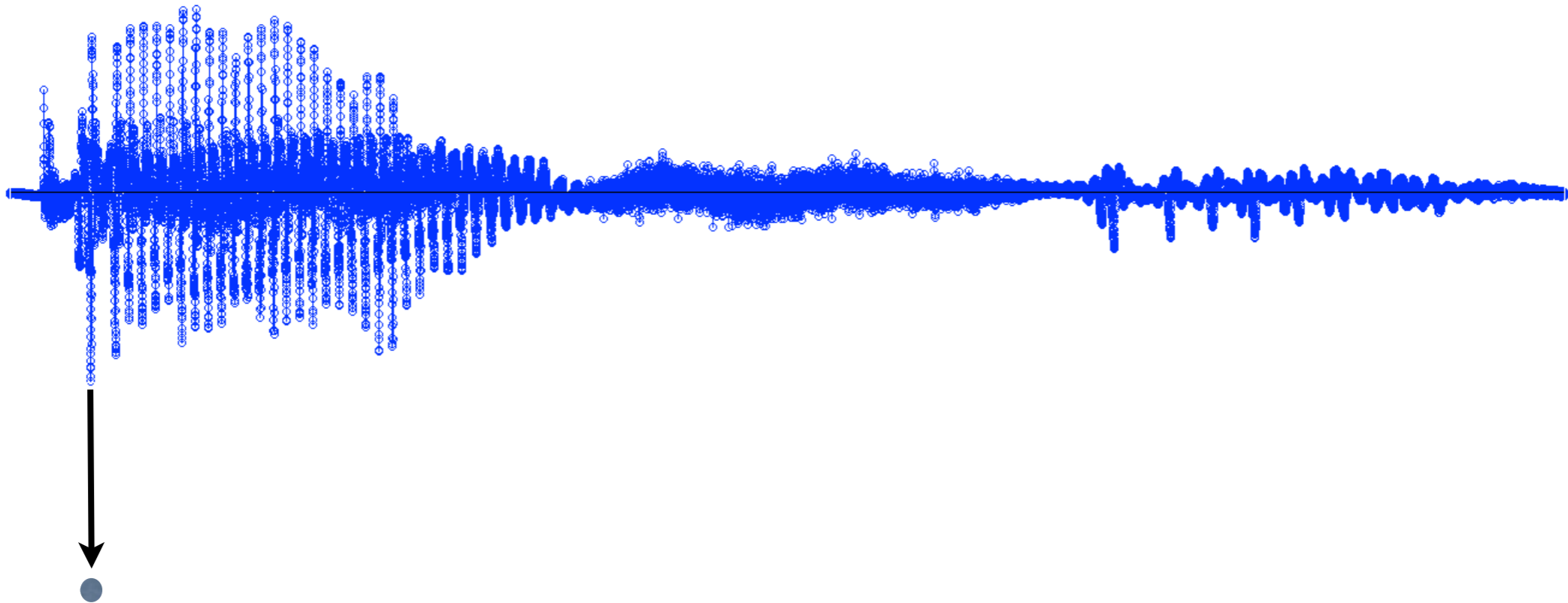
Propiedades de la conversión A/D

Precisión



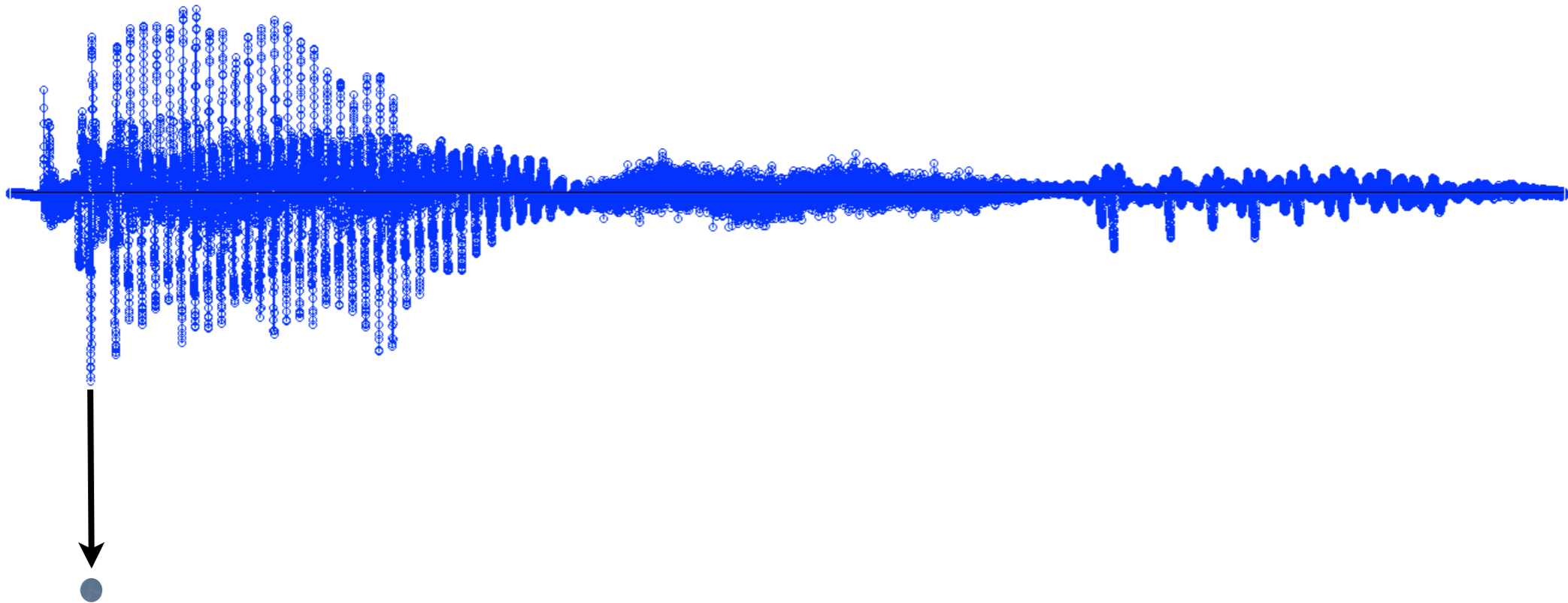
Propiedades de la conversión A/D

Precisión



Propiedades de la conversión A/D

Precisión



Propiedades de la conversión A/D

Precisión



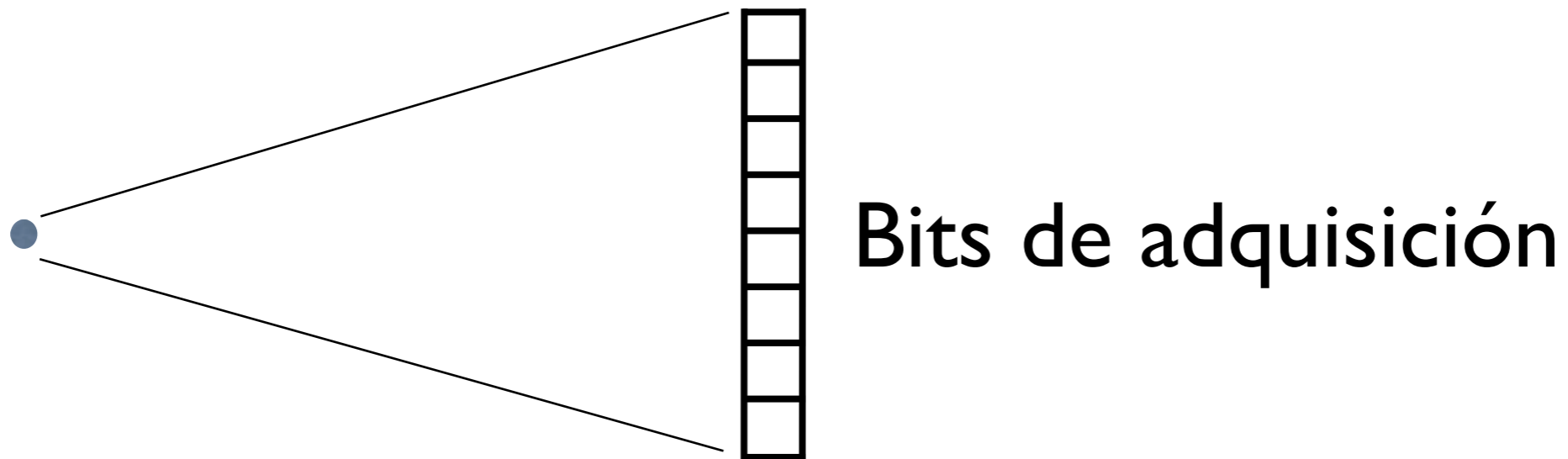
Propiedades de la conversión A/D

Precisión



Propiedades de la conversión A/D

Precisión



Propiedades de la conversión A/D

Precisión

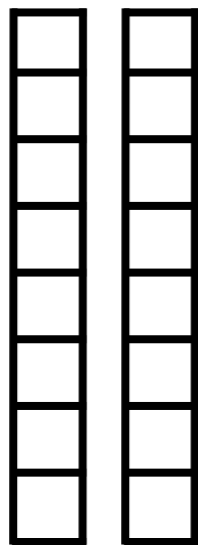
Bits de adquisición

8 bits
(1 byte)



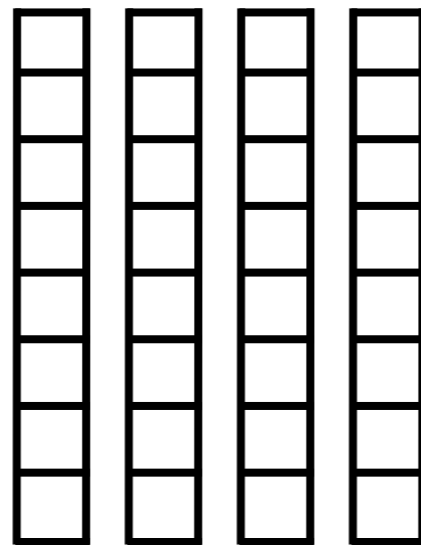
256
valores

16 bits
(2 bytes)



65536
valores

32 bits
(4 bytes)



4.2950e+09
valores

0.00001233862713
0.00001233862804
0.00001233862895
0.00001233862986
⋮

spacing = 0.00000000000091
(1 part in 13 million)

1.000000000
1.000000119
1.000000238
1.000000358
⋮

spacing = 0.000000119
(1 part in 8 million)

1.996093750
1.996093869
1.996093988
1.996094108
⋮

spacing = 0.000000119
(1 part in 17 million)

636.0312500
636.0313110
636.0313720
636.0314331
⋮

spacing = 0.0000610
(1 part in 10 million)

217063424.0
217063440.0
217063456.0
217063472.0

spacing = 16.0
(1 part in 14 million)

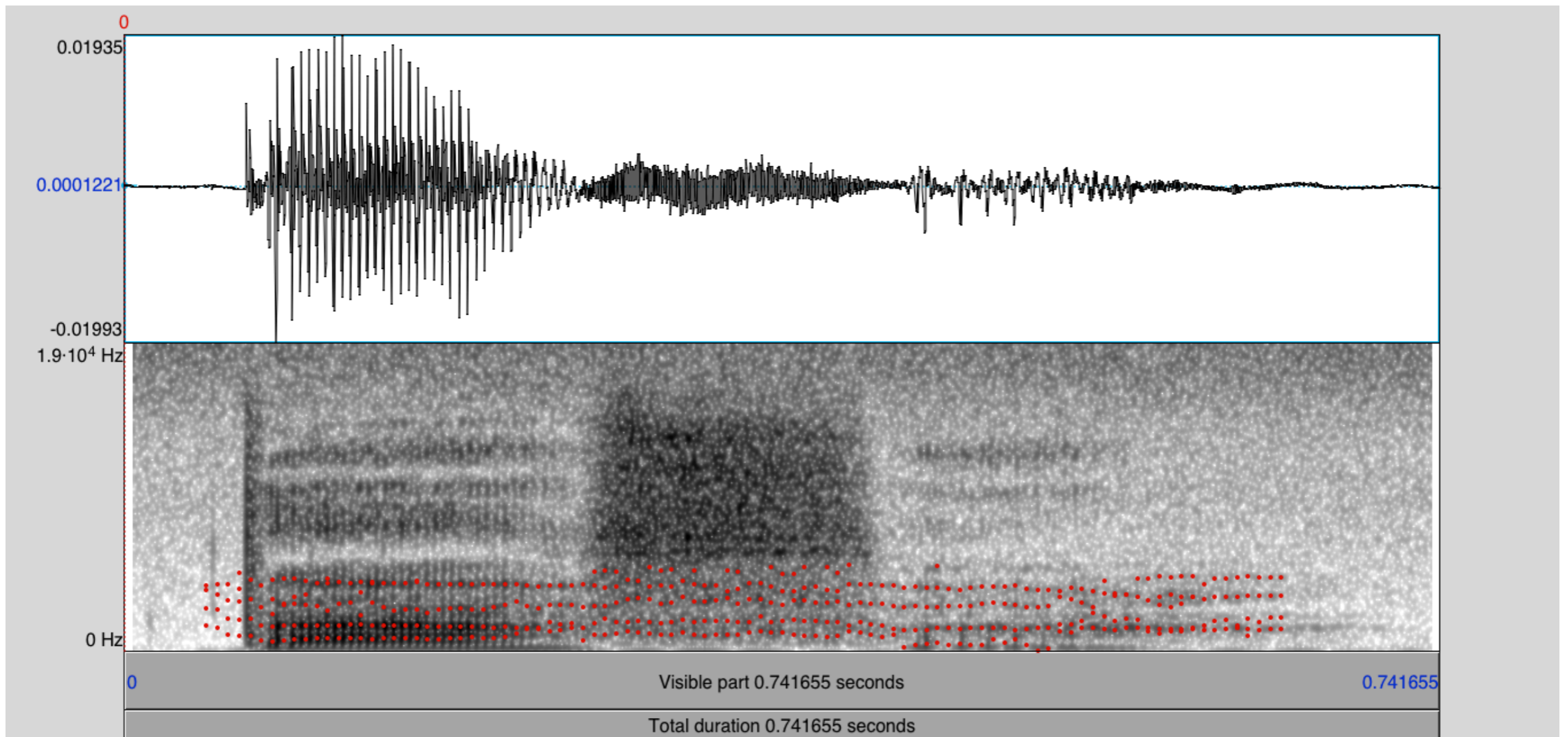
Rango de codificación
(espacio entre valores)

¿De qué dependen las propiedades de muestreo?

¿De qué dependen las propiedades de muestreo?

- 1) De las características naturales de la señal adquirida
- 2) De la información que quiero conservar de la señal original

Propiedades espectrales de la señal



Rango de componentes en frecuencia que contiene una señal
Señal muestreada a 44.100 Hz y 16 bits de precisión

¿De qué dependen las propiedades de muestreo?

¿De qué dependen las propiedades de muestreo?

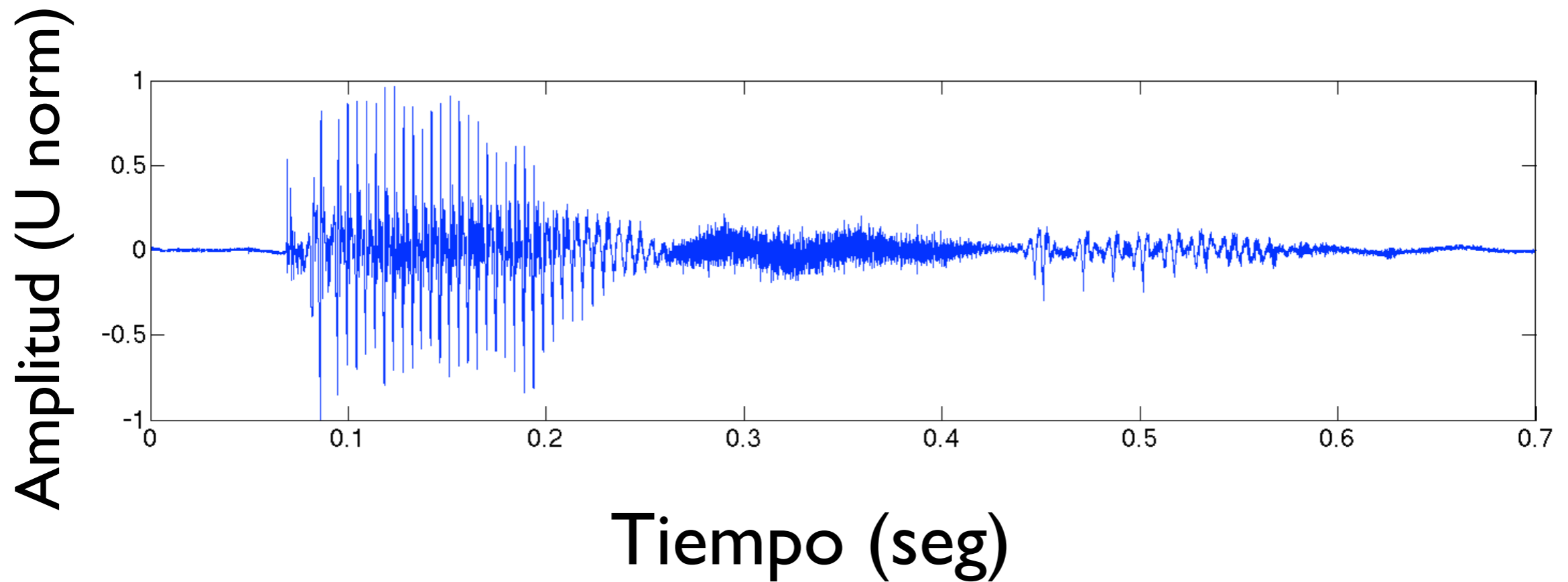
- Debo tener **conocimiento *a priori*** de las características de mi señal de interés

Representación de señales

- **Elección de la variable independiente:**

- -Señales en el *dominio* (función) del tiempo
- -Señales en el *dominio* (función) de la frecuencia
- -Señales en el *dominio* del tiempo y la frecuencia

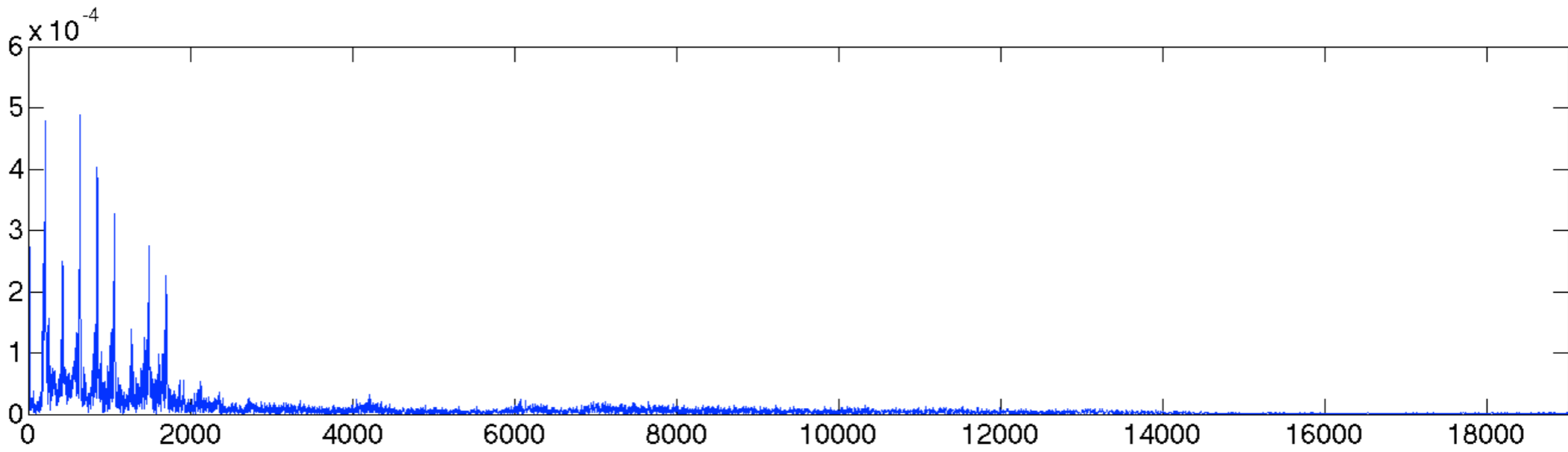
Señal en el dominio del tiempo



Señal en el dominio de la frecuencia

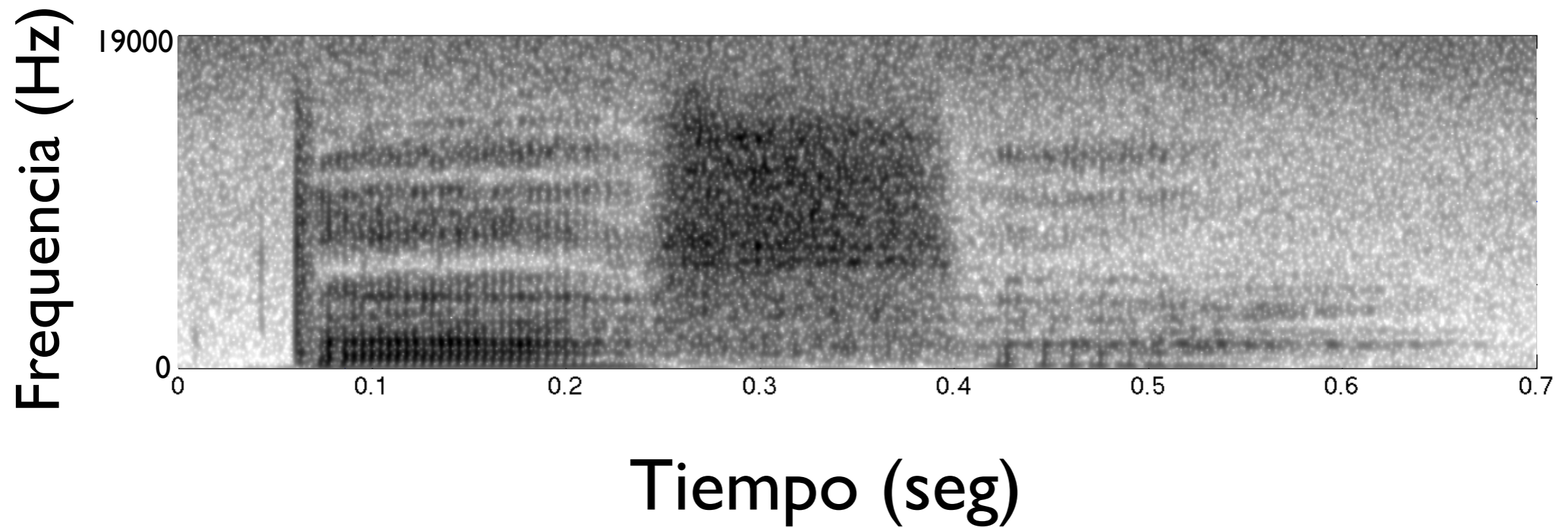
Amplitud del espectro

$|Y(\tau)|$



Frecuencia (Hz)

Señal en el dominio del tiempo y la frecuencia

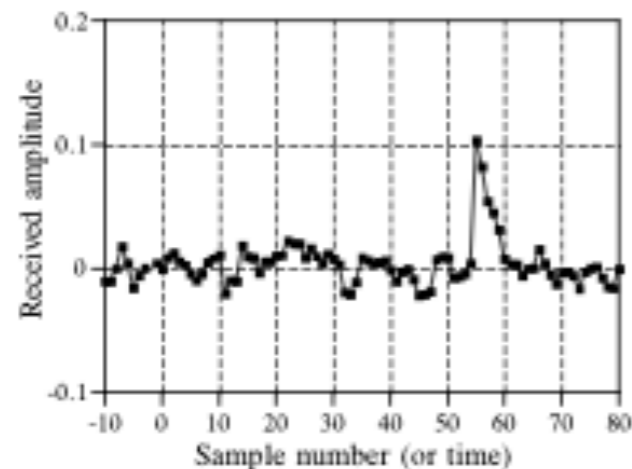
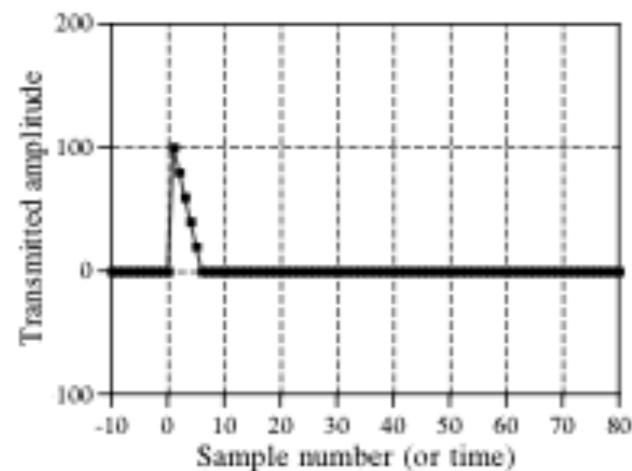


Análisis espectral

Correlación

Dadas dos señales:

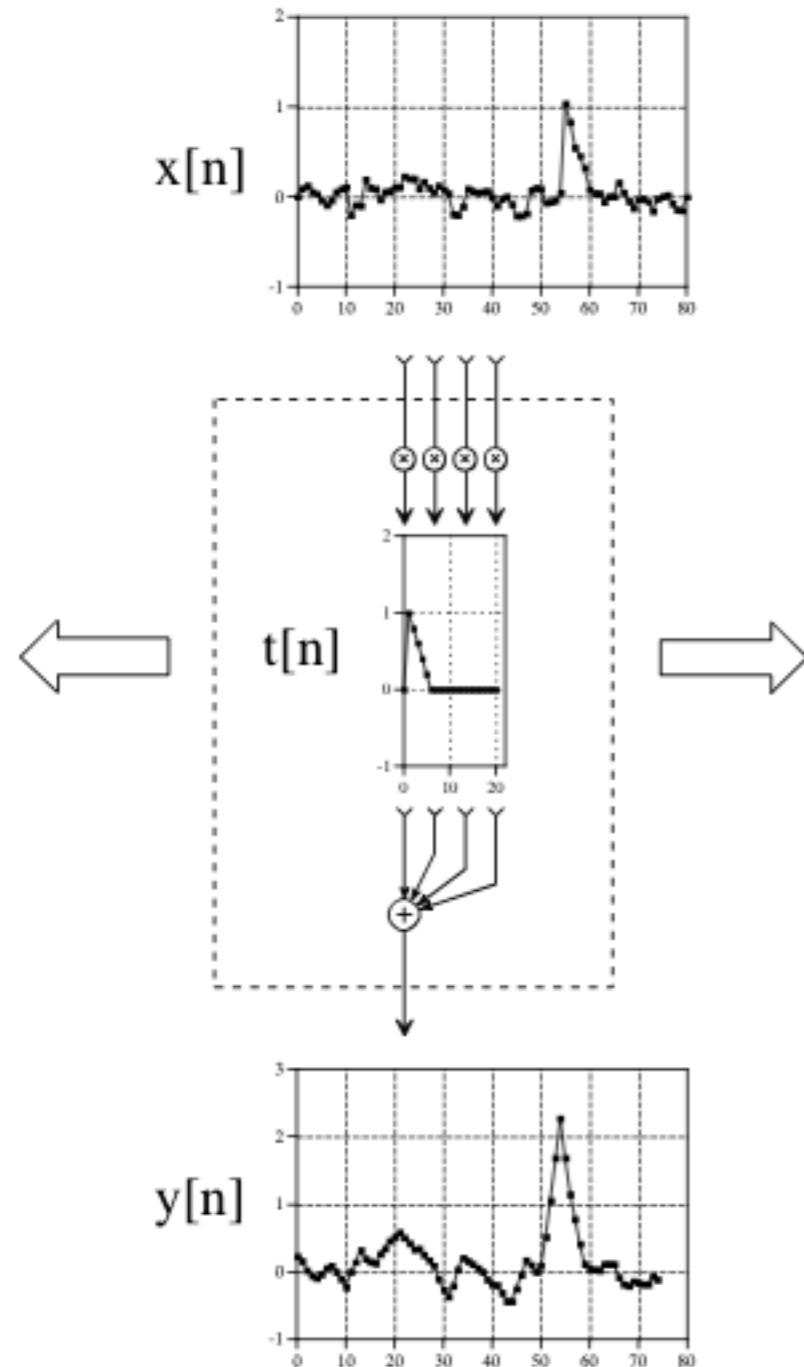
Problema:



Dada una señal de forma conocida, ¿Cual es la forma mejor forma de determinar si la misma señal está -y dónde- contenida en otra señal?

En otras palabras: ¿cuanto y dónde se parece una señal a otra?

Correlación



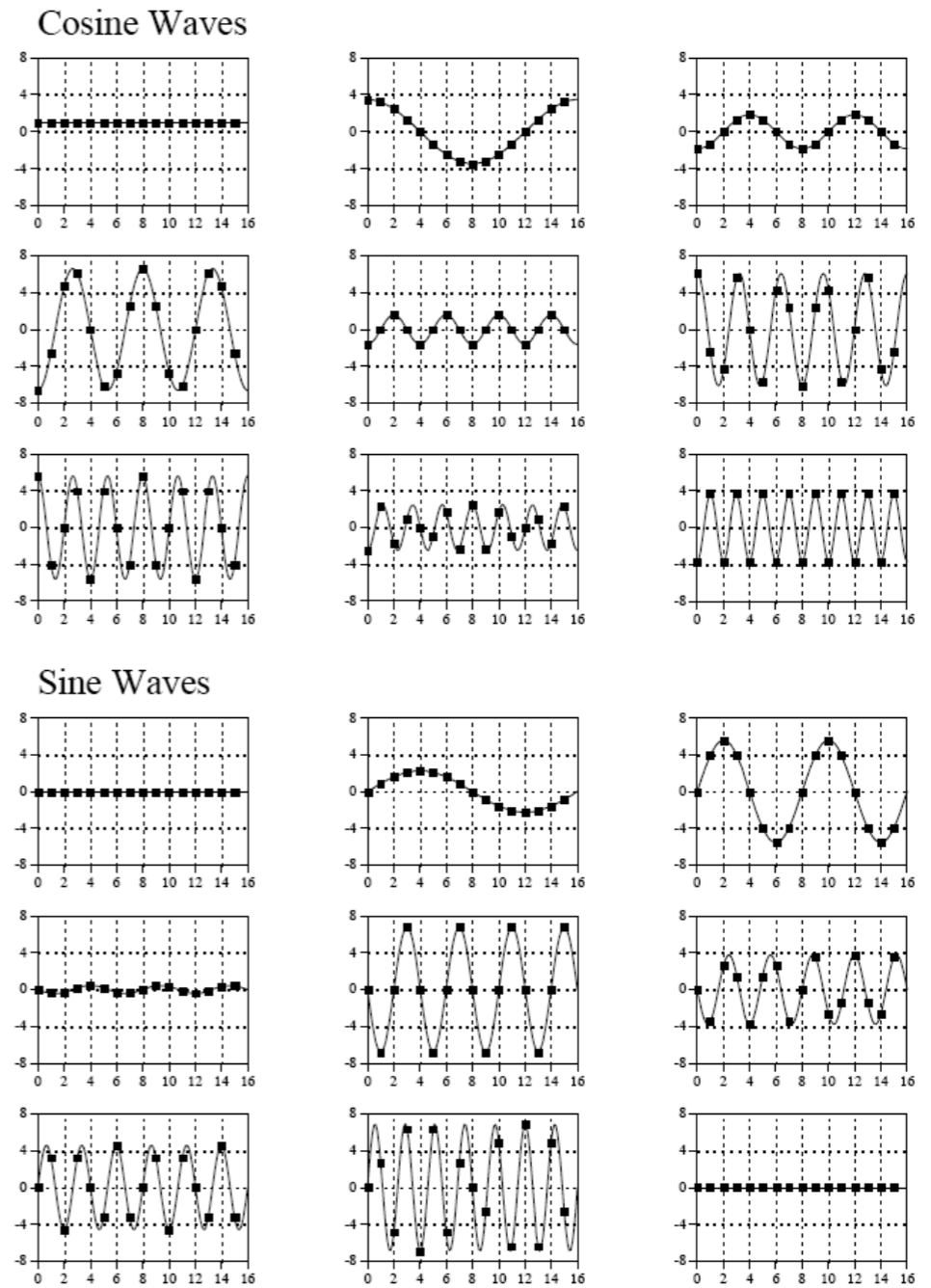
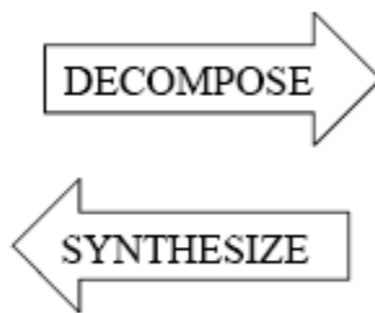
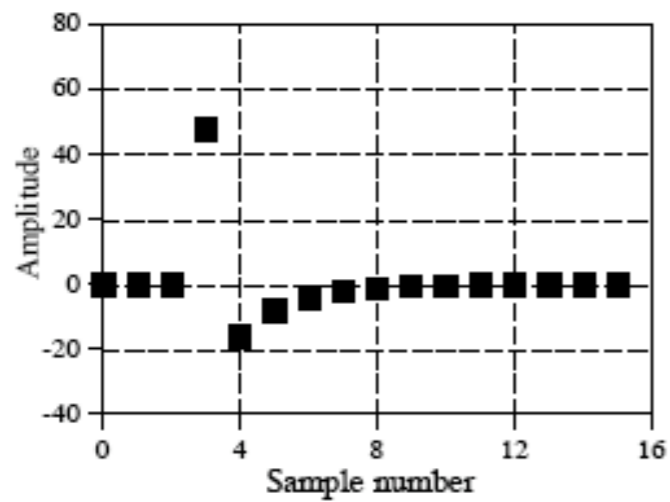
$$y[n] = \sum_{n=1}^N x[n]t[n-\tau]$$

Análisis espectral

- Fourier

- Es una familia de técnicas matemáticas, basadas en la descomposición de señales *en sinusoides*.
- Trabajar con señales que son más fáciles de manejar matemáticamente que la señal original.

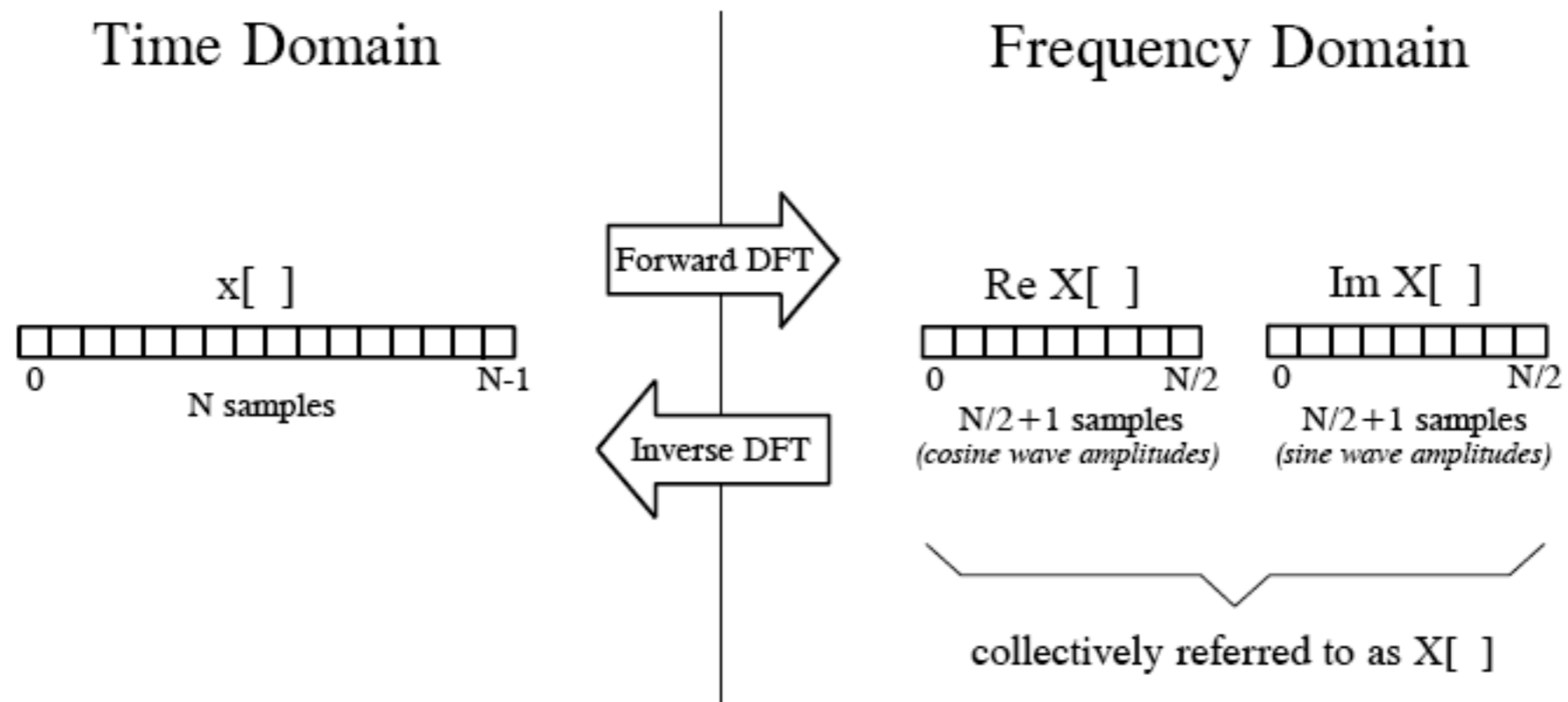
Fourier



Fourier

- Transforma una señal de entrada de N puntos en dos señales de salida de $N/2+1$ puntos.
- La señal de entrada contiene la señal que será descompuesta (dominio del tiempo), mientras que las dos señales de salida contienen las amplitudes de los senos y cosenos que la componen (dominio de la frecuencia).

Fourier



Funciones base de la transformada de Fourier

EQUATION 8-1

Equations for the DFT basis functions. In these equations, $c_k[i]$ and $s_k[i]$ are the cosine and sine waves, each N points in length, running from $i = 0$ to $N-1$. The parameter, k , determines the frequency of the wave. In an N point DFT, k takes on values between 0 and $N/2$.

$$c_k [i] = \cos(2\pi ki/N)$$

$$s_k [i] = \sin(2\pi ki/N)$$

Ecuaciones de la transformación de Fourier

- Perspectiva de la correlación

EQUATION 8-4

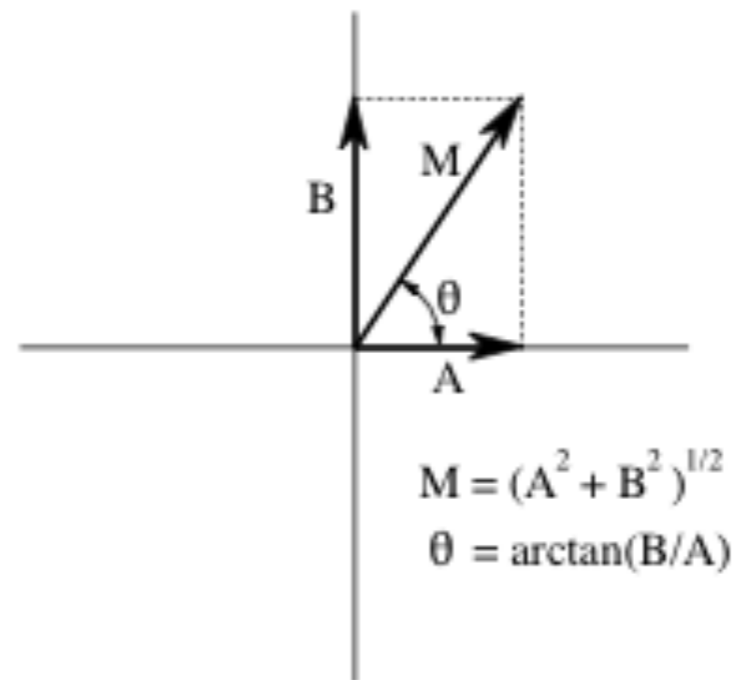
The analysis equations for calculating the DFT. In these equations, $x[i]$ is the time domain signal being analyzed, and $ReX[k]$ & $ImX[k]$ are the frequency domain signals being calculated. The index i runs from 0 to $N-1$, while the index k runs from 0 to $N/2$.

$$ReX[k] = \sum_{i=0}^{N-1} x[i] \cos(2\pi k i / N)$$

$$ImX[k] = - \sum_{i=0}^{N-1} x[i] \sin(2\pi k i / N)$$

Representación cartesiana y polar

FIGURE 8-9
Rectangular-to-polar conversion. The addition of a cosine wave and a sine wave (of the same frequency) follows the same mathematics as the addition of simple vectors.



EQUATION 8-6
Rectangular-to-polar conversion. The rectangular representation of the frequency domain, $ReX[k]$ and $ImX[k]$, is changed into the polar form, $MagX[k]$ and $PhaseX[k]$.

$$MagX[k] = (ReX[k]^2 + ImX[k]^2)^{1/2}$$

$$PhaseX[k] = \arctan\left(\frac{ImX[k]}{ReX[k]}\right)$$

EQUATION 8-7
Polar-to-rectangular conversion. The two arrays, $MagX[k]$ and $PhaseX[k]$, are converted into $ReX[k]$ and $ImX[k]$.

$$ReX[k] = MagX[k] \cos(PhaseX[k])$$

$$ImX[k] = MagX[k] \sin(PhaseX[k])$$

Relación de Euler

EQUATION 30-11

Euler's relation. This is a key equation for using complex numbers in science and engineering.

$$e^{jx} = \cos x + j \sin x$$

Representación compleja de sinusoides

$$A \cos(\omega t) + B \sin(\omega t) \rightleftharpoons a + jb$$

(conventional representation) *(complex number)*

$$M \cos(\omega t + \phi) \rightleftharpoons M e^{j\theta}$$

(conventional representation) *(complex number)*

Ecuación de Fourier

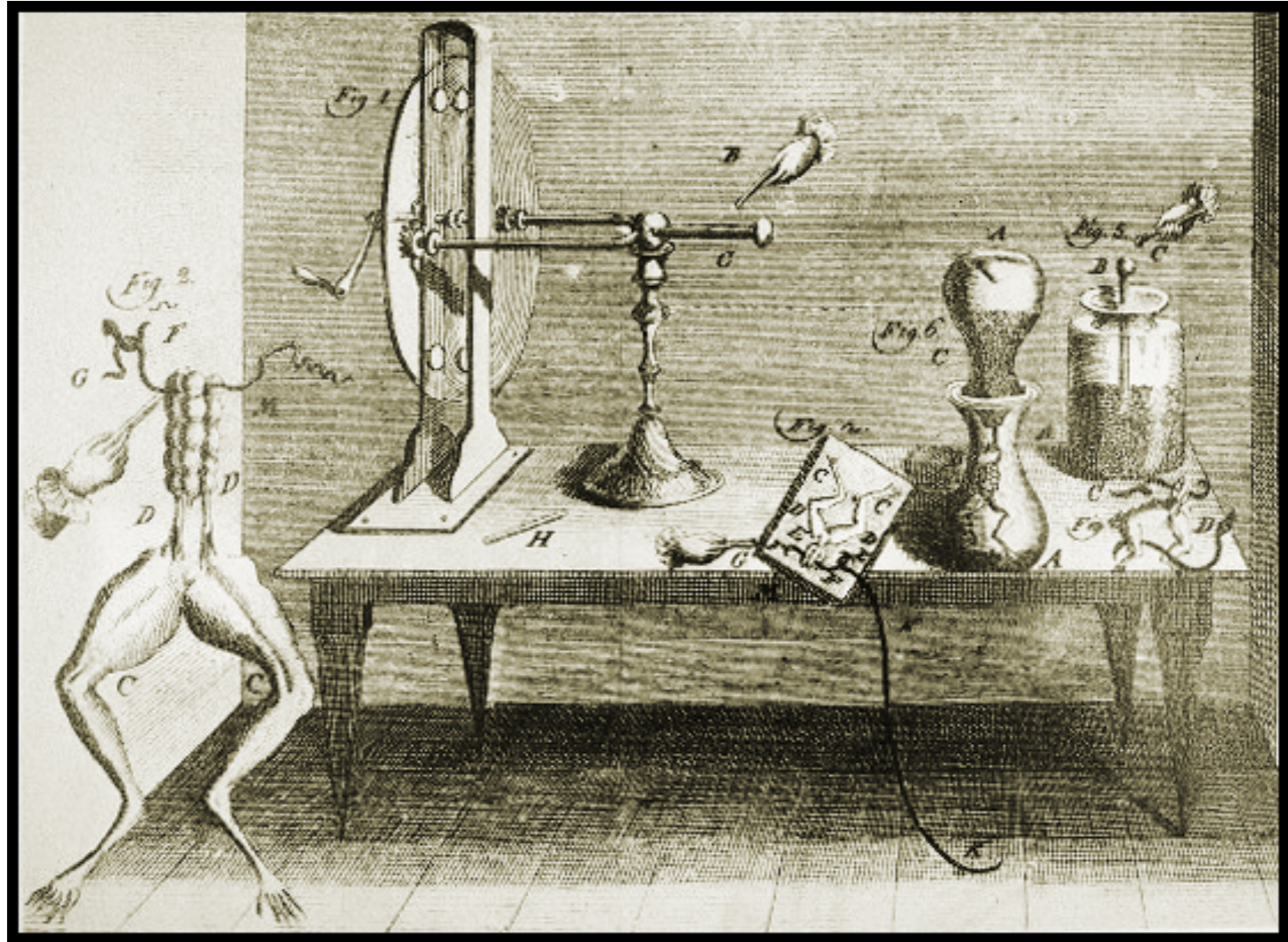
$$\hat{f}(\xi) = \int_{-\infty}^{\infty} f(x) e^{-2\pi i x \xi} dx$$

Señales electrofisiológicas

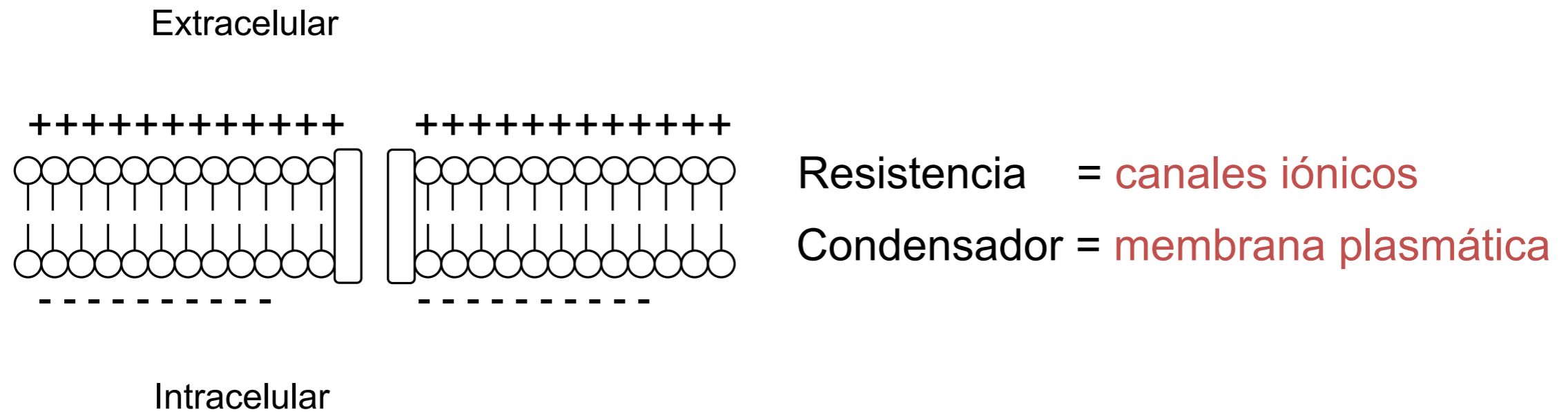
Los organismos vivos producen actividad eléctrica



Luigi Galvani
1737-1798



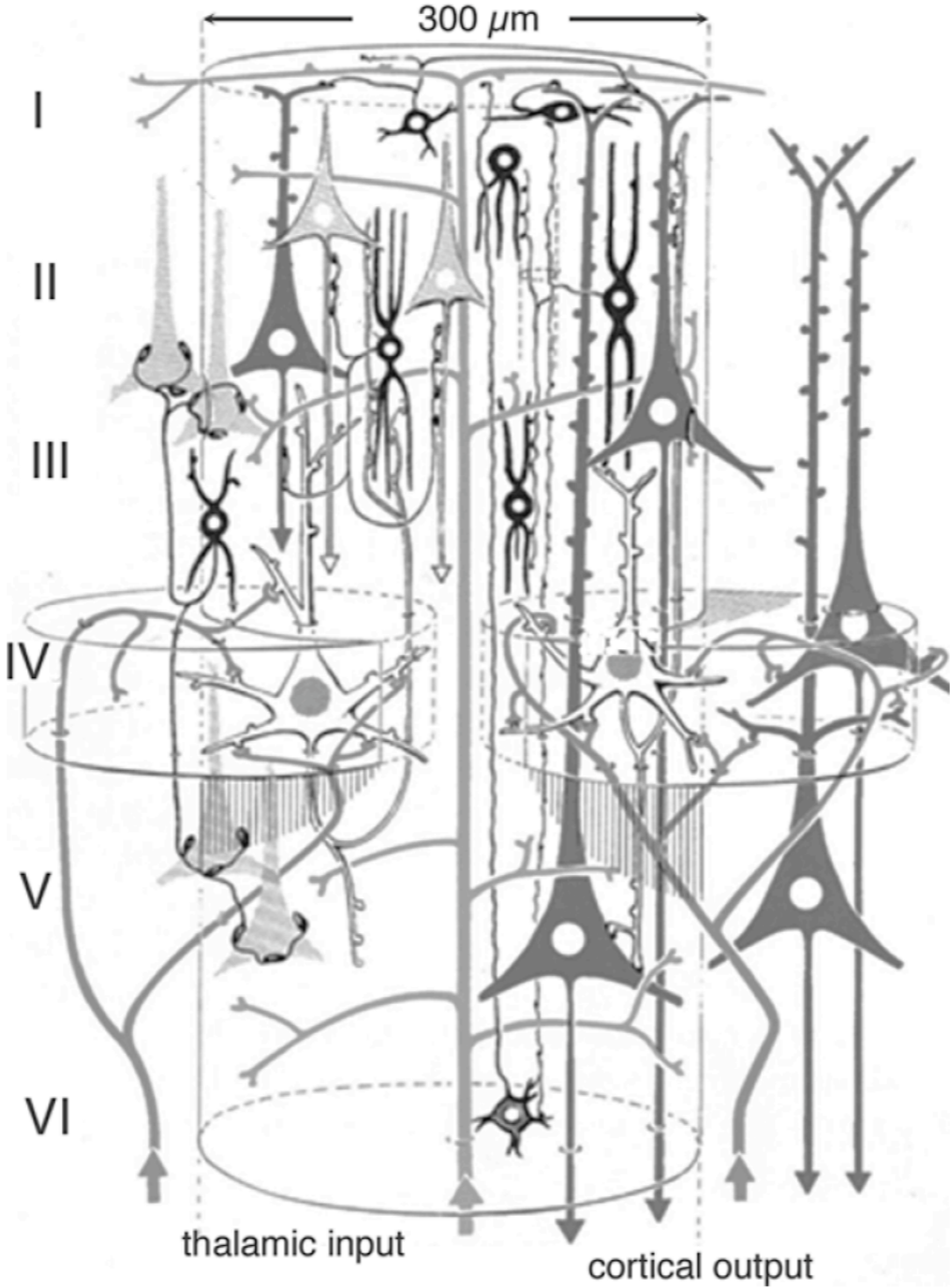
La neurona como circuito generador de corrientes



Resistencia (Ω) = distintos tipos de canales iónicos en la membrana de distintas células, con distintas velocidades de apertura y cierre.

Capacitancia (F) = dependiente del tamaño de la membrana de las distintas células.

Esquema simplificado de una columna cortical



Flujos de corriente en el axón y la dendrita

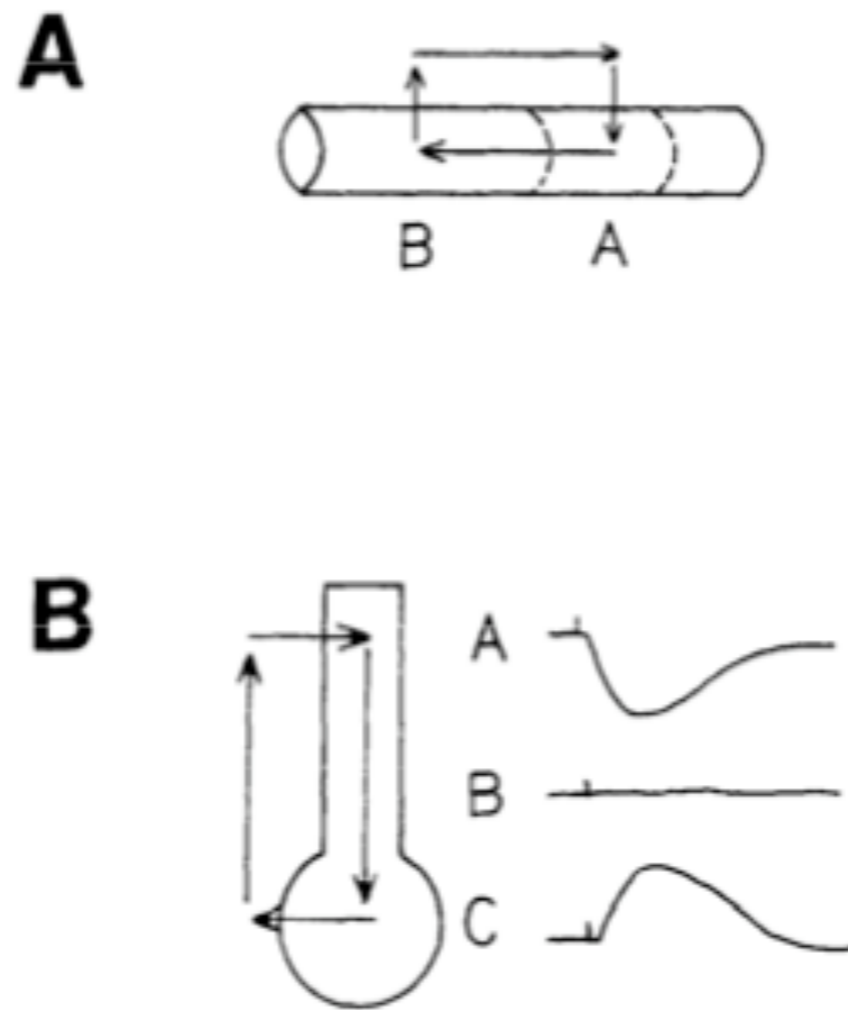
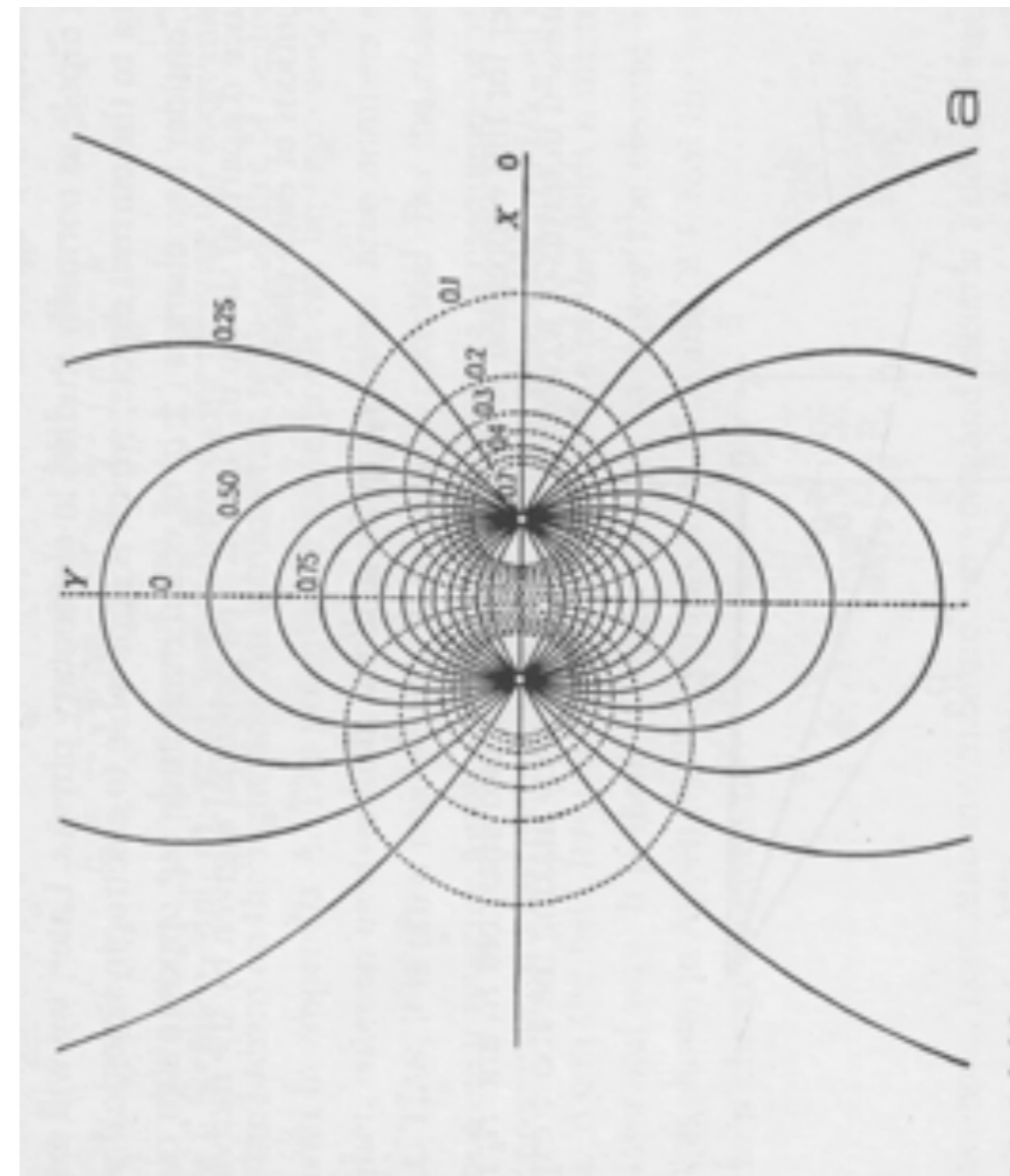
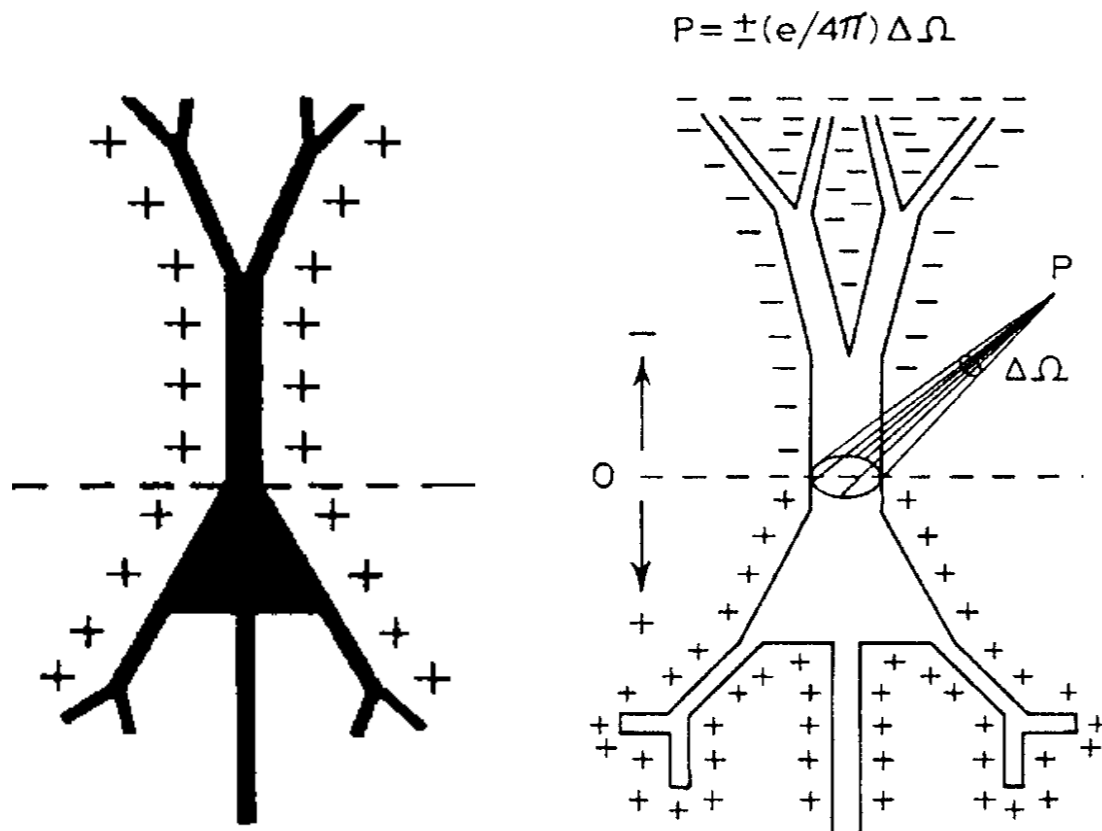
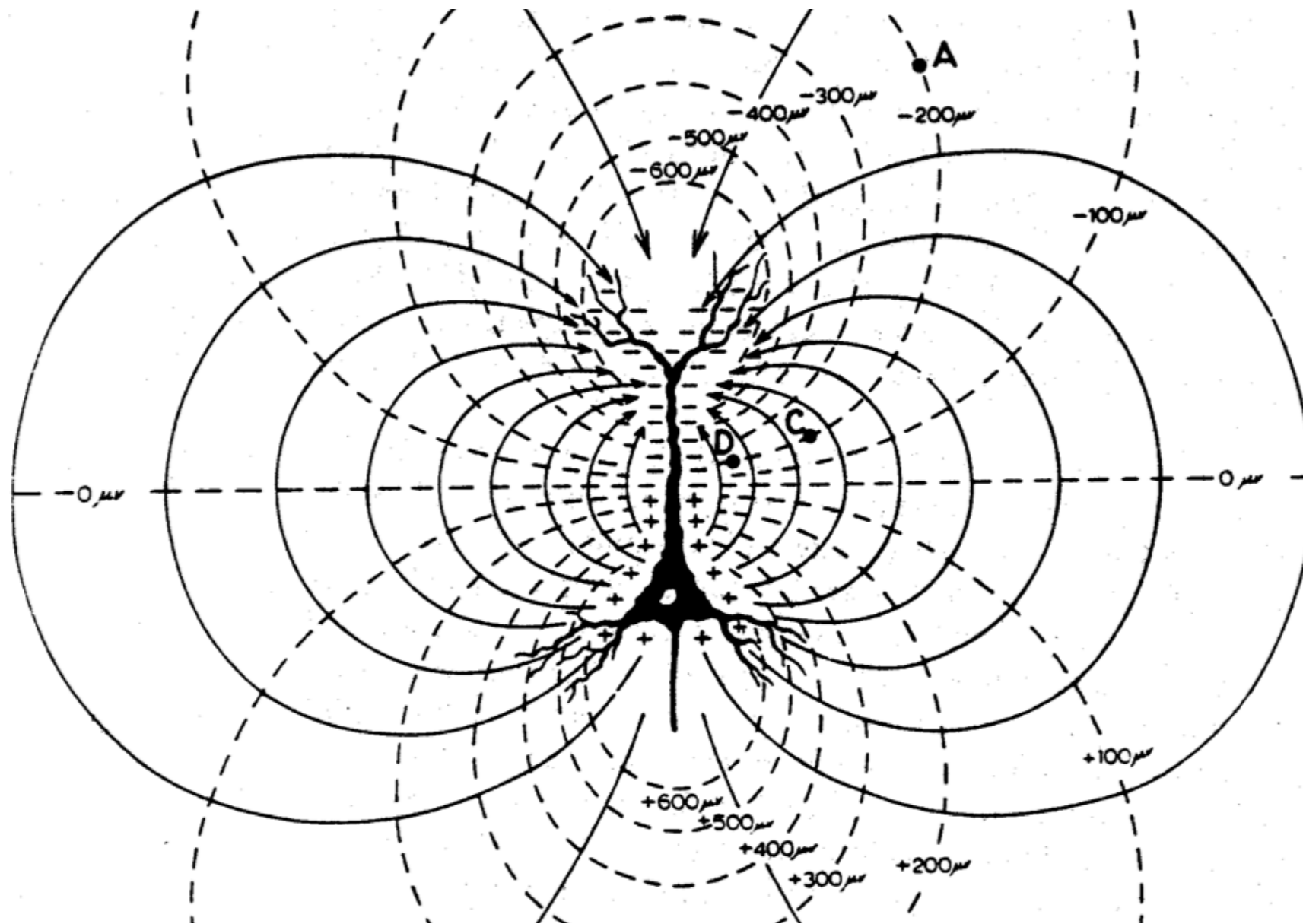


Fig. 1. (A) Current flows in a closed loop when an action potential begins at point A (with inward sodium currents). Passive currents exit at point B. (B) Synaptic excitation at the distal dendrites drives a current loop that flows from positive (point C) to negative potentials (point A) in the extracellular medium. Response transients, positive upward.

Principio de la generación de corrientes extracelulares en el tejido cerebral



Principio de generación del LFP



El modelo del campo generado depende del tipo de neurona y de la configuración espacial

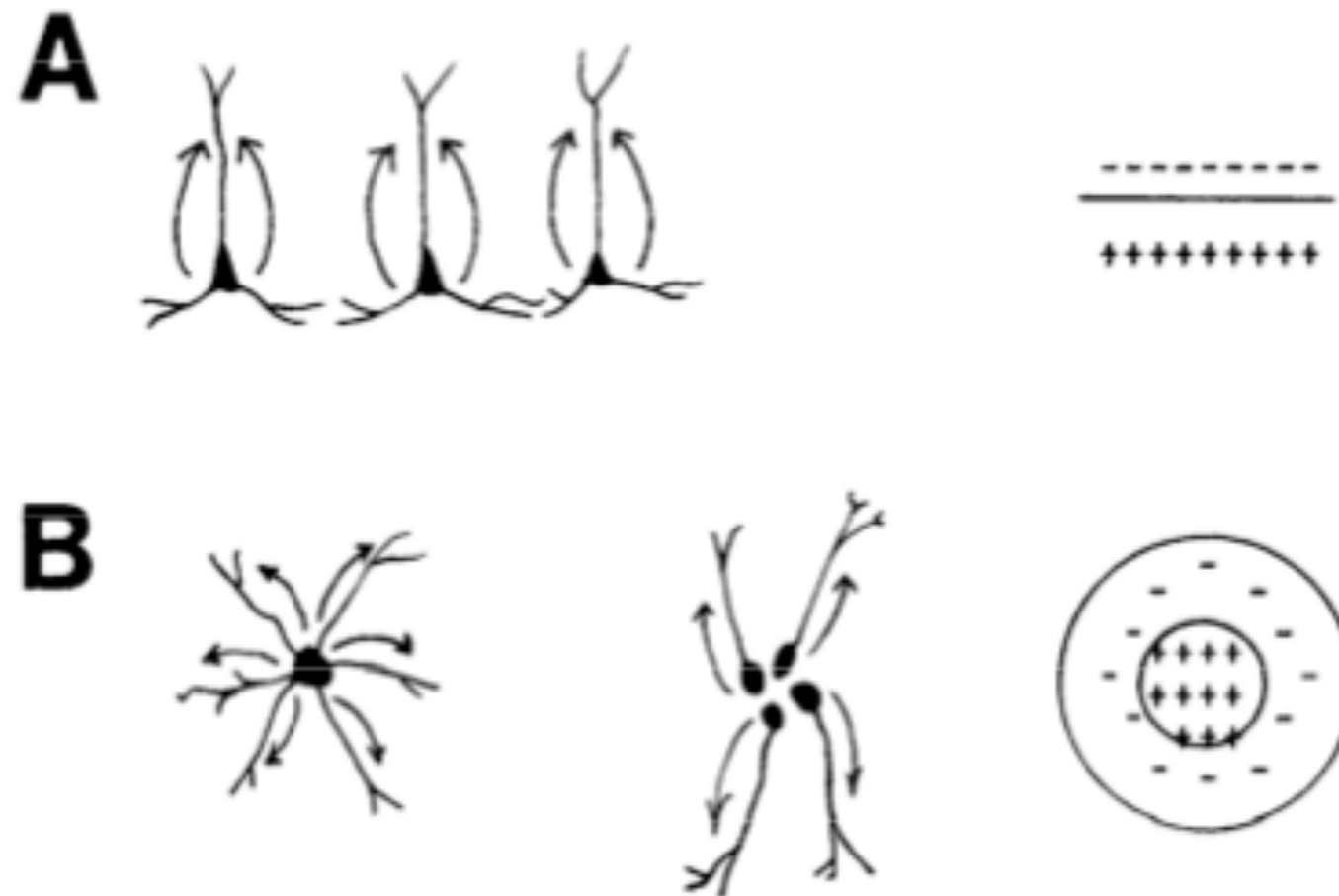
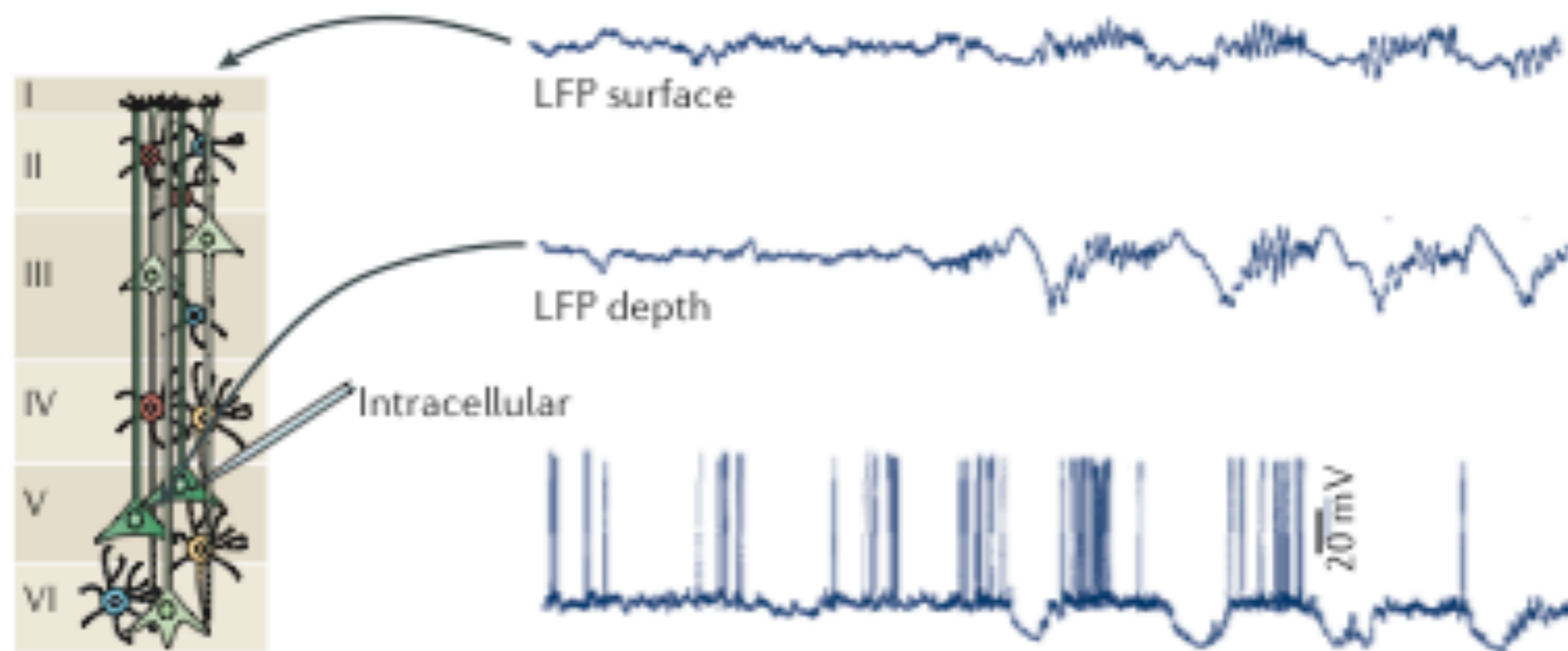
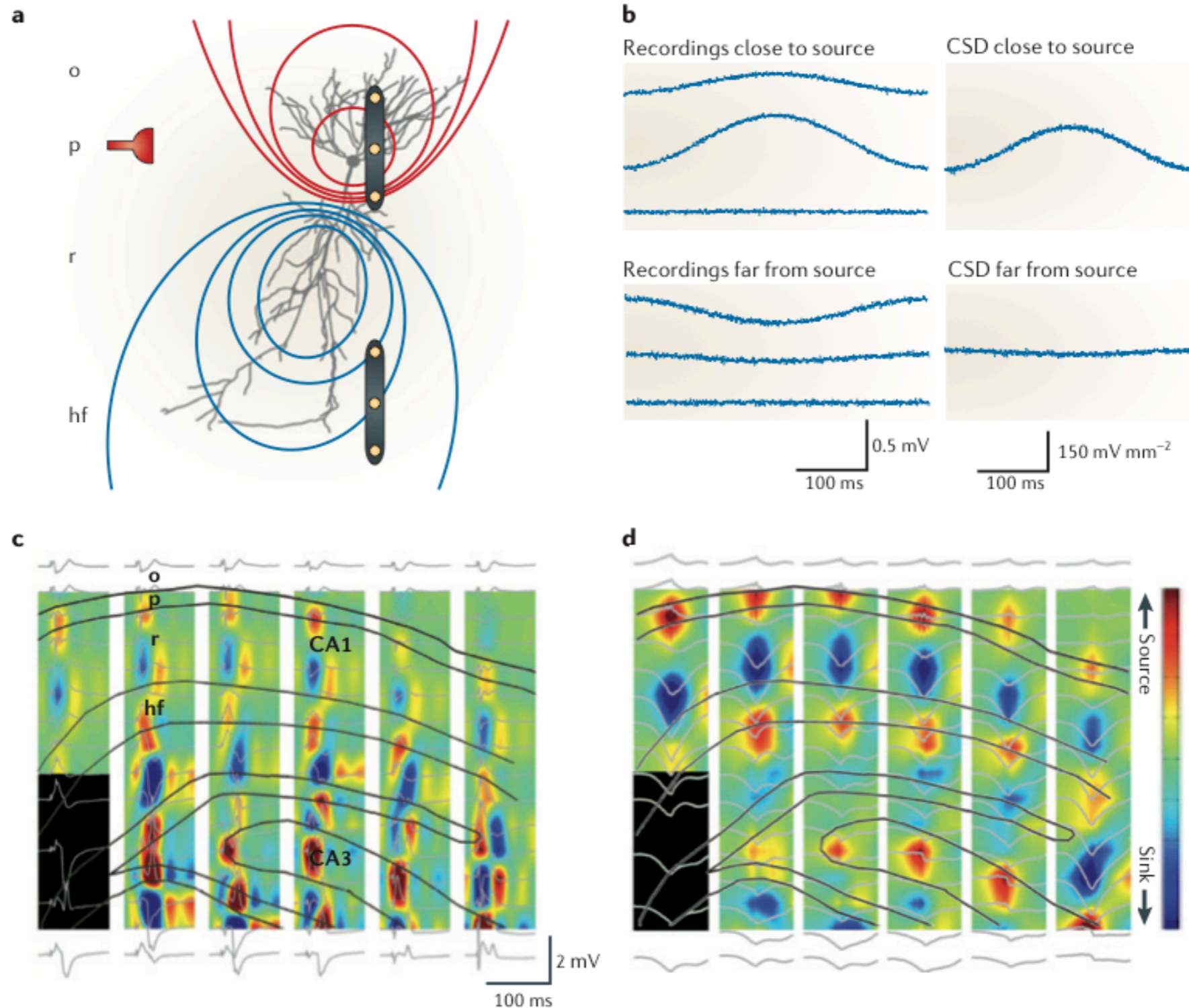


Fig. 3. (A) Excitation of the distal apical dendrites of pyramidal cells gives rise to mainly axial currents; the electrostatic model is a dipole layer that gives an open field. (B) Excitation of the distal dendrites of a single stellate cell or excitation of the periperal dendrites of cells in a nuclear structure gives rise to radial currents; the electrostatic model is one of concentric layers of charges that generate a closed field.

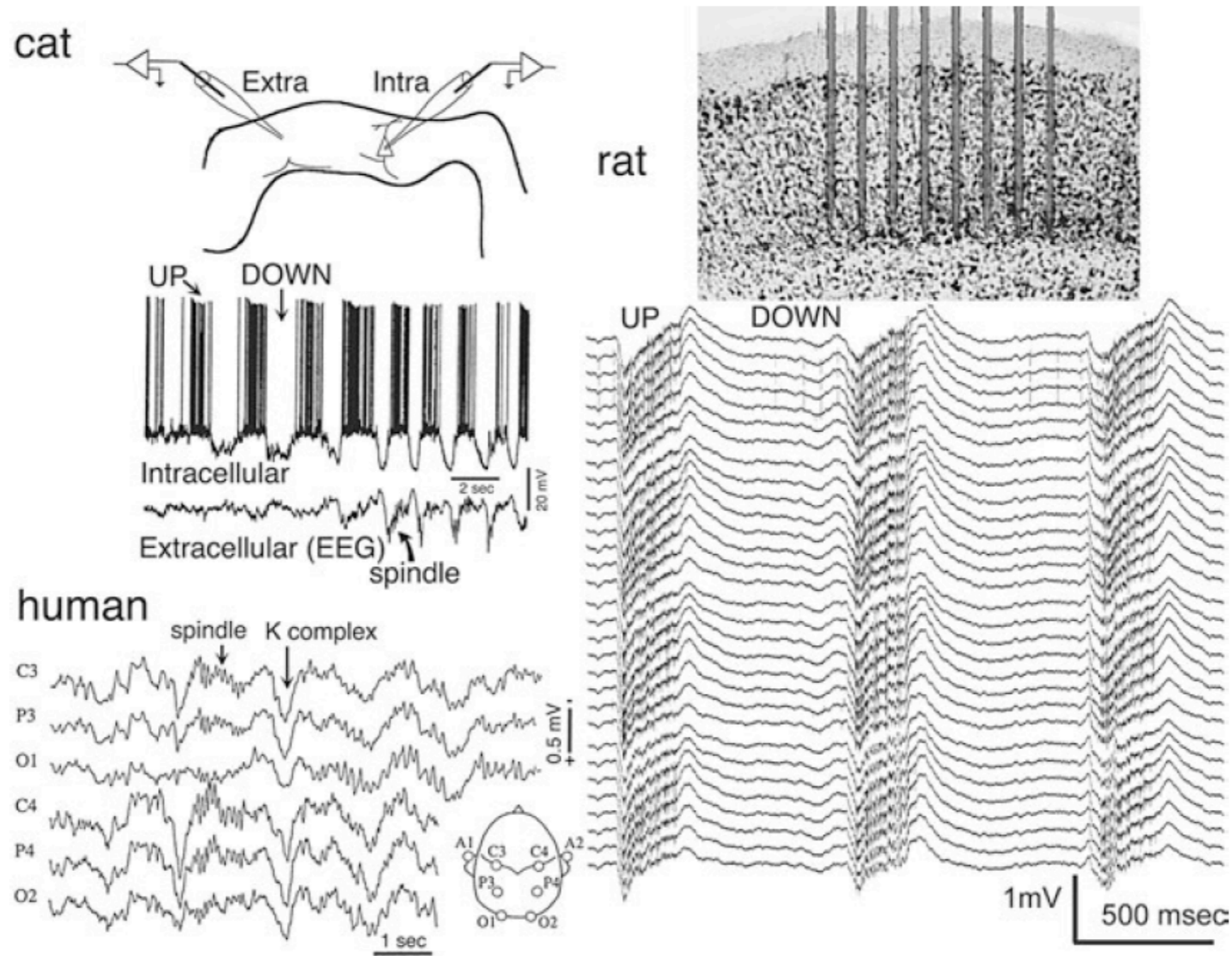
Registro del LFP con diferentes técnicas



Current source density



Las neuronas oscilan entre estados de alta y baja probabilidad de excitabilidad



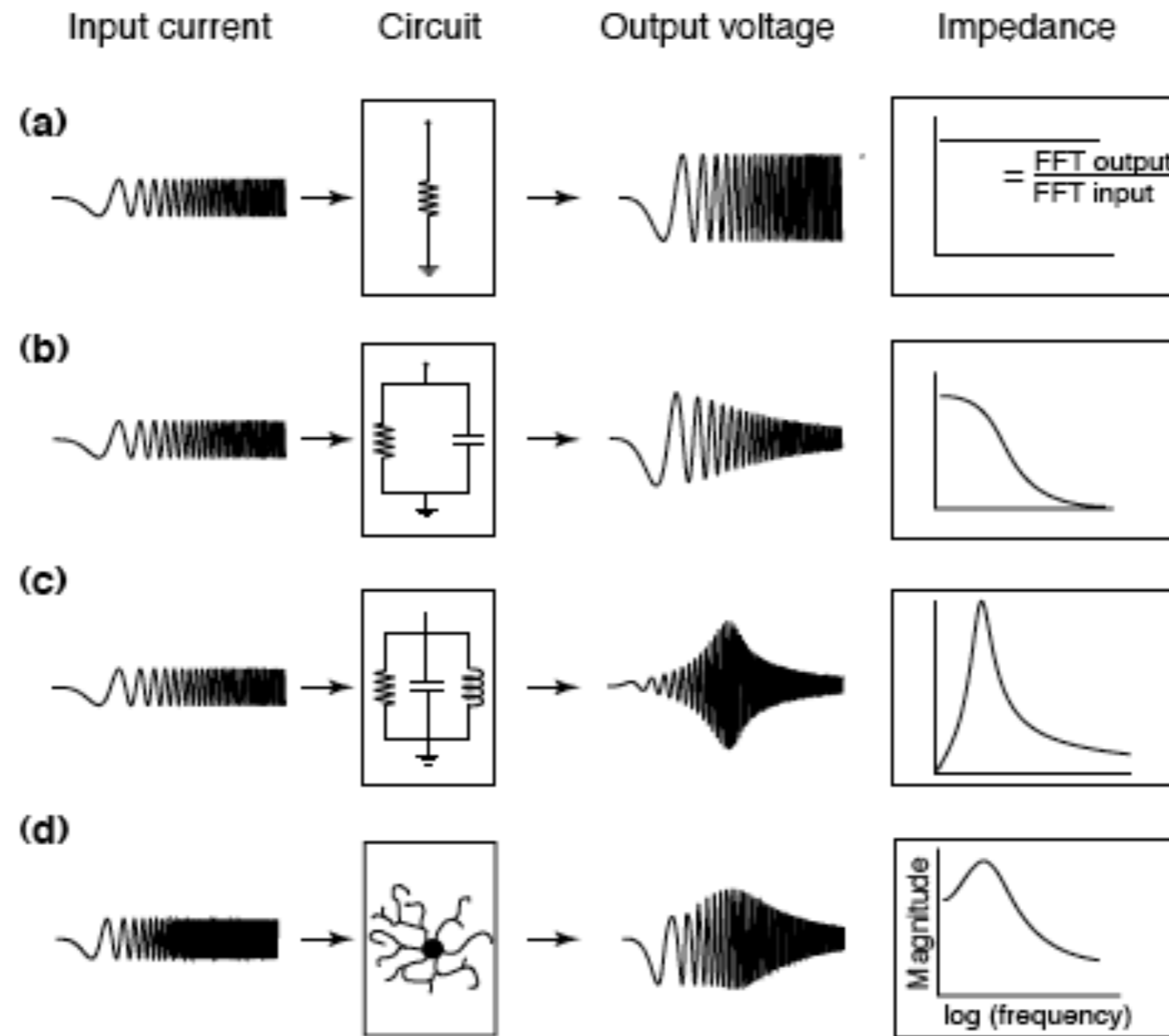
¿Que determina el rango de frecuencia característica de cada ritmo cerebral?

A grandes razgos, existen dos explicaciones:

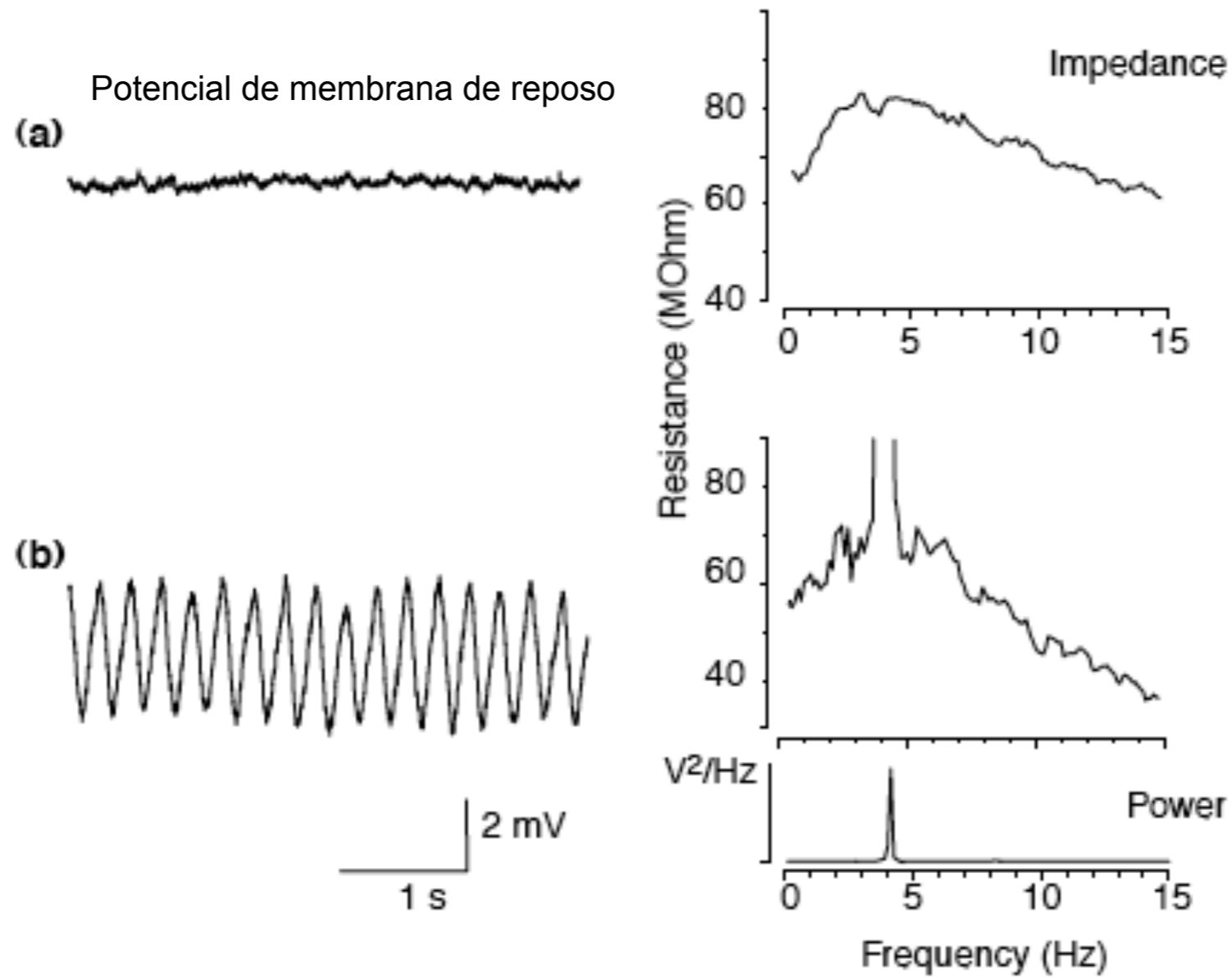
Una invoca a patrones de conectividad entre neuronas, y las propiedades dinámicas de las sinapsis que intervienen, de tal forma que circuitos de neuronas principales (excitatorias), conectadas con interneuronas inhibitorias generen patrones rítmicos de retroalimentación (activación-inhibición) que producen actividad oscilatoria en neuronas fundamentalmente no oscilantes (Traub R.D. et al. 1991).

Otra explicación, sugiere que la ritmicidad de redes de neuronas se origina a partir del acoplamiento de subunidades oscilatorias, cada una de las cuales posee preferencia por una frecuencia, determinada intrínsecamente (Llinás R. 1988).

RESONANCIA NEURONAL ES UNA PROPIEDAD DE LA IMPEDANCIA



Preferencia por frecuencias de neuronas de la oliva inferior

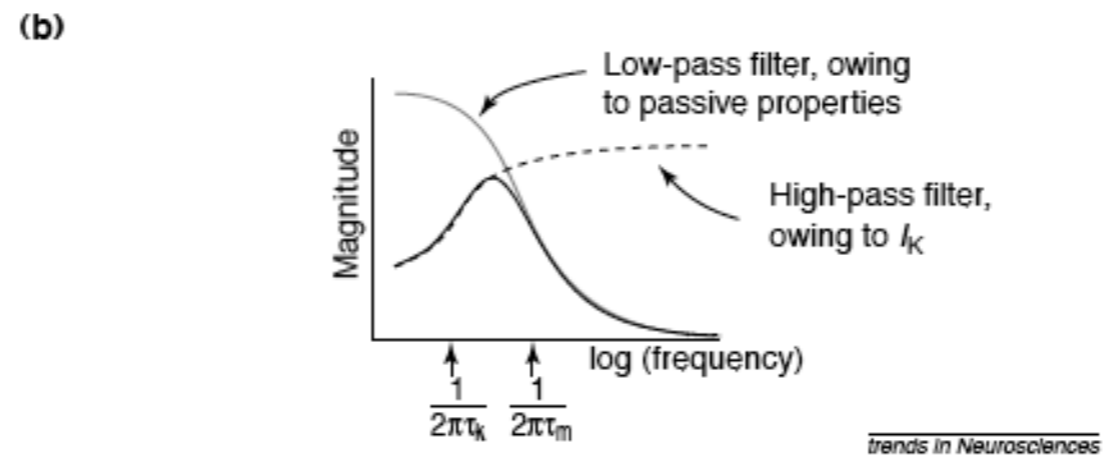
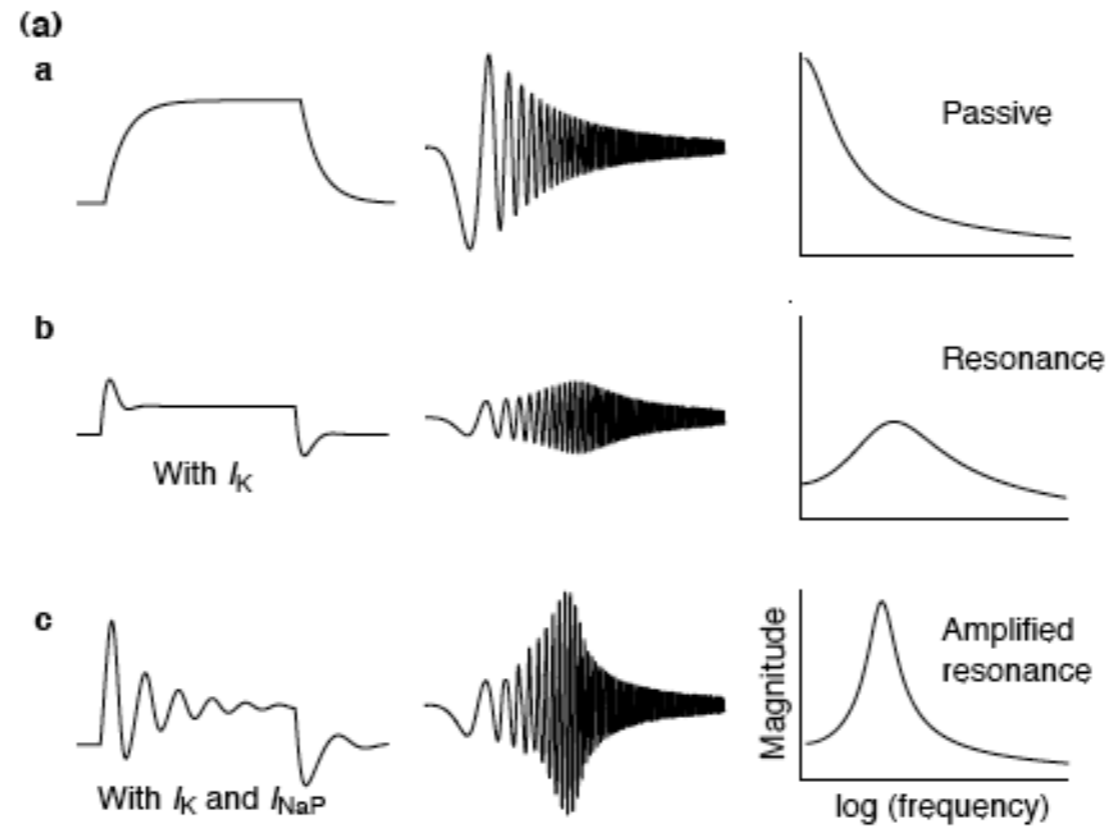


Los canales iónicos están involucrados en la generación intrínseca de oscilaciones del potencial de membrana

Las oscilaciones subumbral del potencial de membrana observadas en neuronas de la oliva inferior son dependientes de la presencia de corrientes de Calcio activadas por Bajo-Voltaje (I_T currents).

Tanto las oscilaciones como la resonancia neuronal son eliminadas por bloqueo farmacológico de I_T

Combinación de propiedades activas (pasa-alto) y pasivas (pasa-bajo) para generar resonancia en neuronas



Interneuronas a distancia permiten la generación de oscilaciones robustas

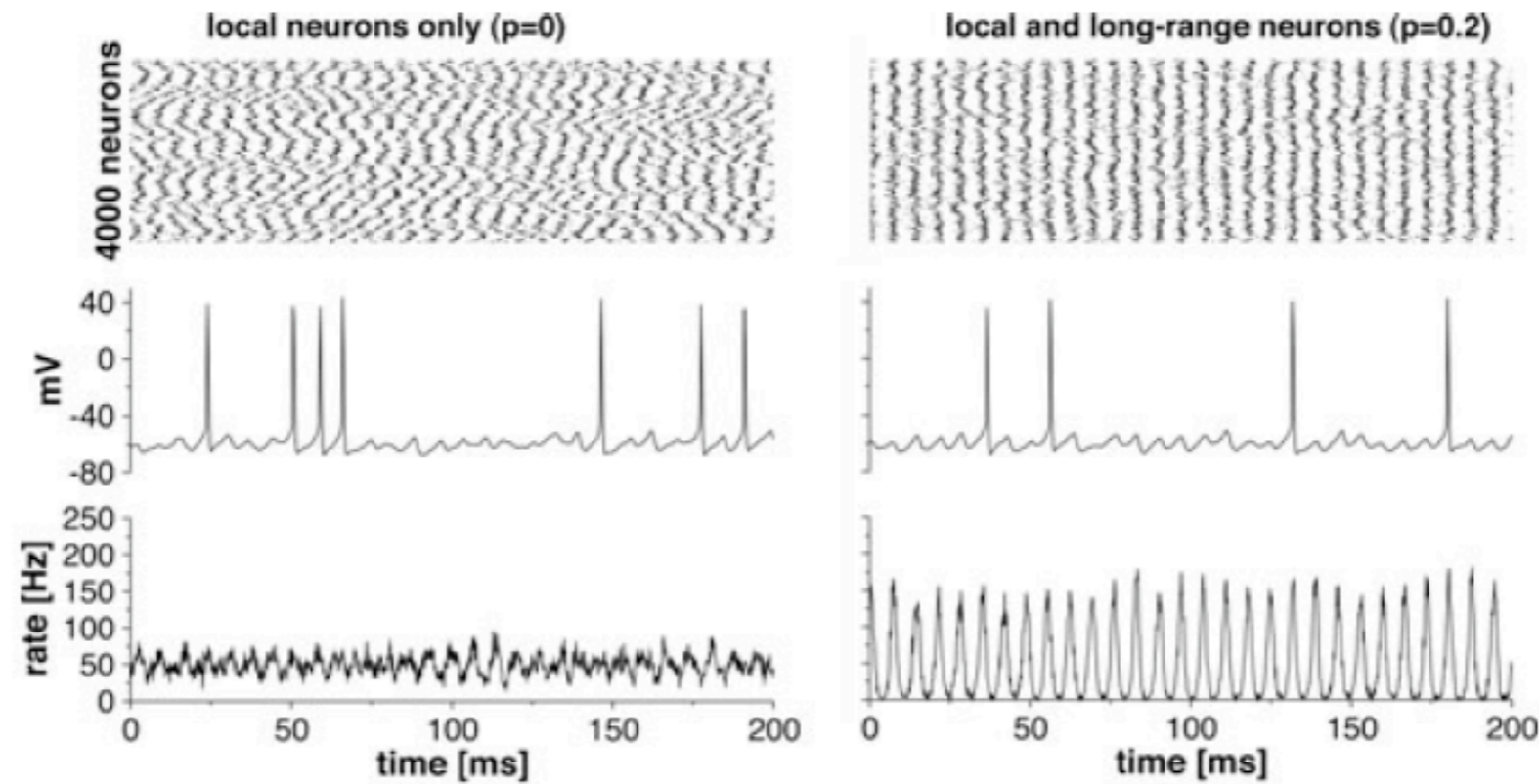


Figure 3.9. In networks with only local inhibitory connections, no oscillations emerge (left: top, spike raster of individual neurons; middle, voltage trace of a single representative cell; bottom, population synchrony). Adding a small subset of long-range interneurons to the locally connected population, with 20 percent of the contacts distributed according to a power-law distribution, robust oscillation emerges (right). Reprinted, with permission, from Buzsáki et al. (2004).

Algunas configuraciones ...

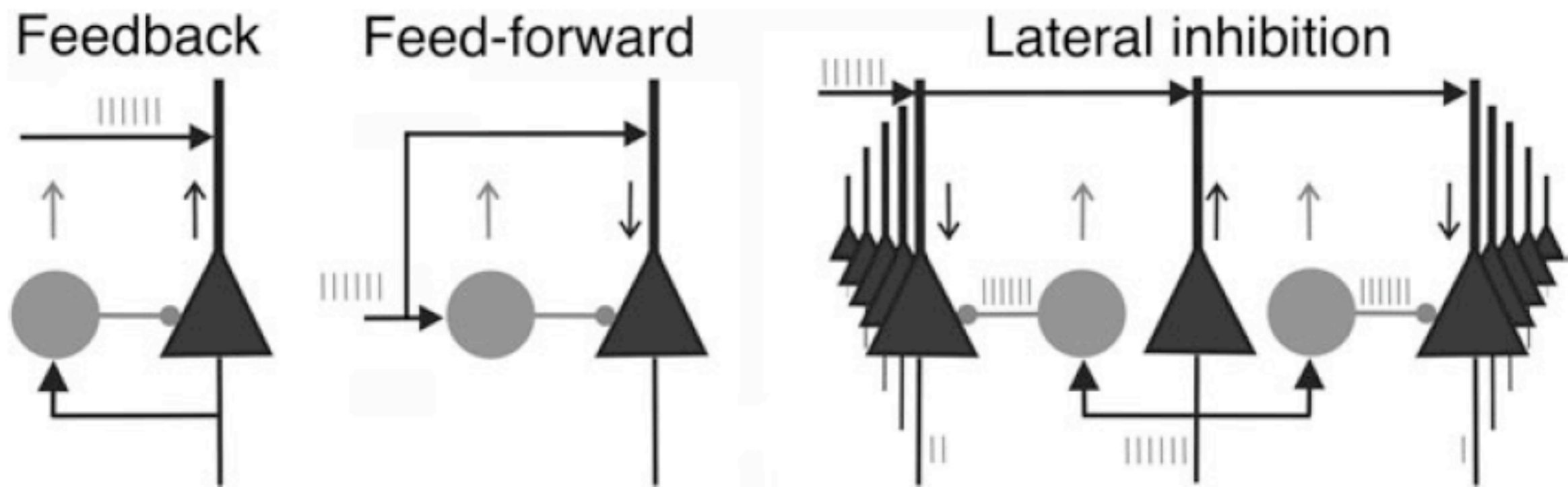


Figure 3.2. Negative (inhibitory) feedback provides stability. Feedforward inhibition dampens (“filters”) the effect of afferent excitation. Lateral inhibition provides autonomy (segregation) of neurons by suppressing the similarly activated neighboring neurons (“winner take all”).

Circuiteria básica

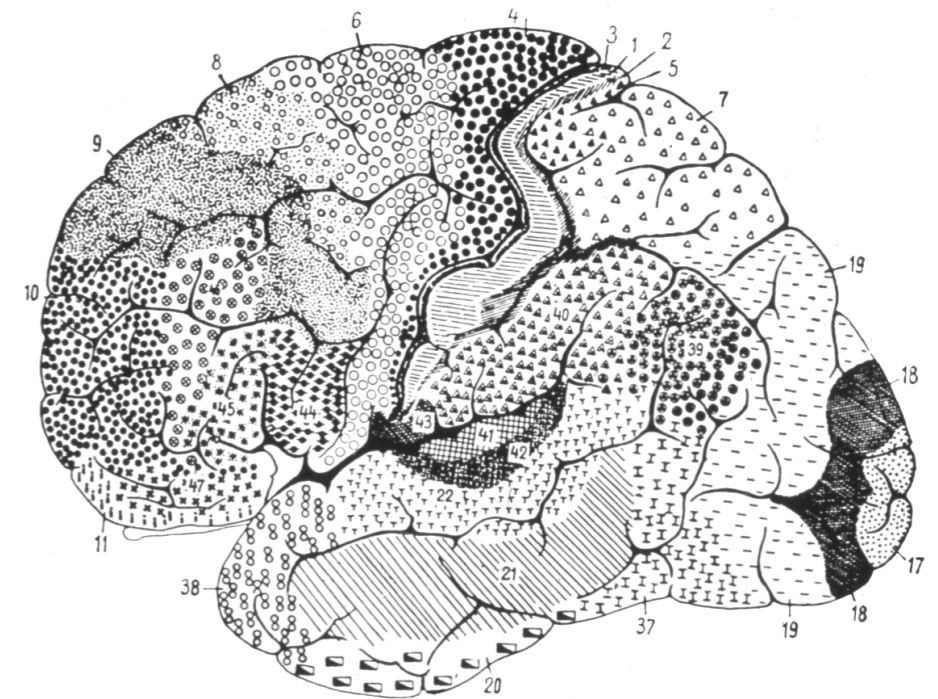
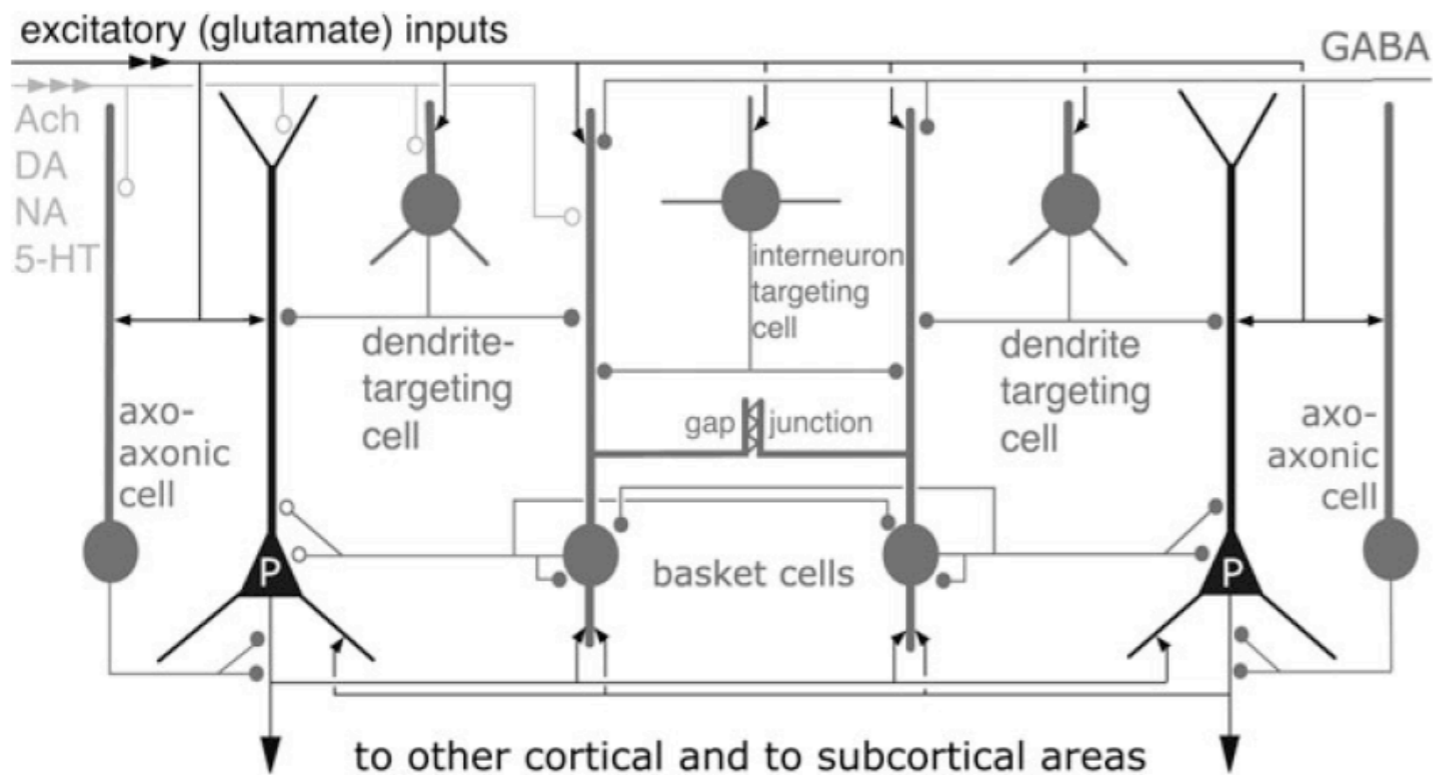


Figure 3.6. The basic cortical circuit, including one type of pyramidal cell (P) and representative interneuron classes. Perisomatic control of pyramidal cell is secured by basket and axoaxonic (chandelier) neurons. Both pyramidal cells and interneurons are innervated by extracircuit excitatory and inhibitory inputs as well as by subcortical neurotransmitters: acetylcholine (ACh), dopamine (DA), norepinephrine (NA), and serotonin (5-HT, 5-hydroxytryptamine). Modified, with permission, from Somogyi et al. (1998).

Patrones de conectividad

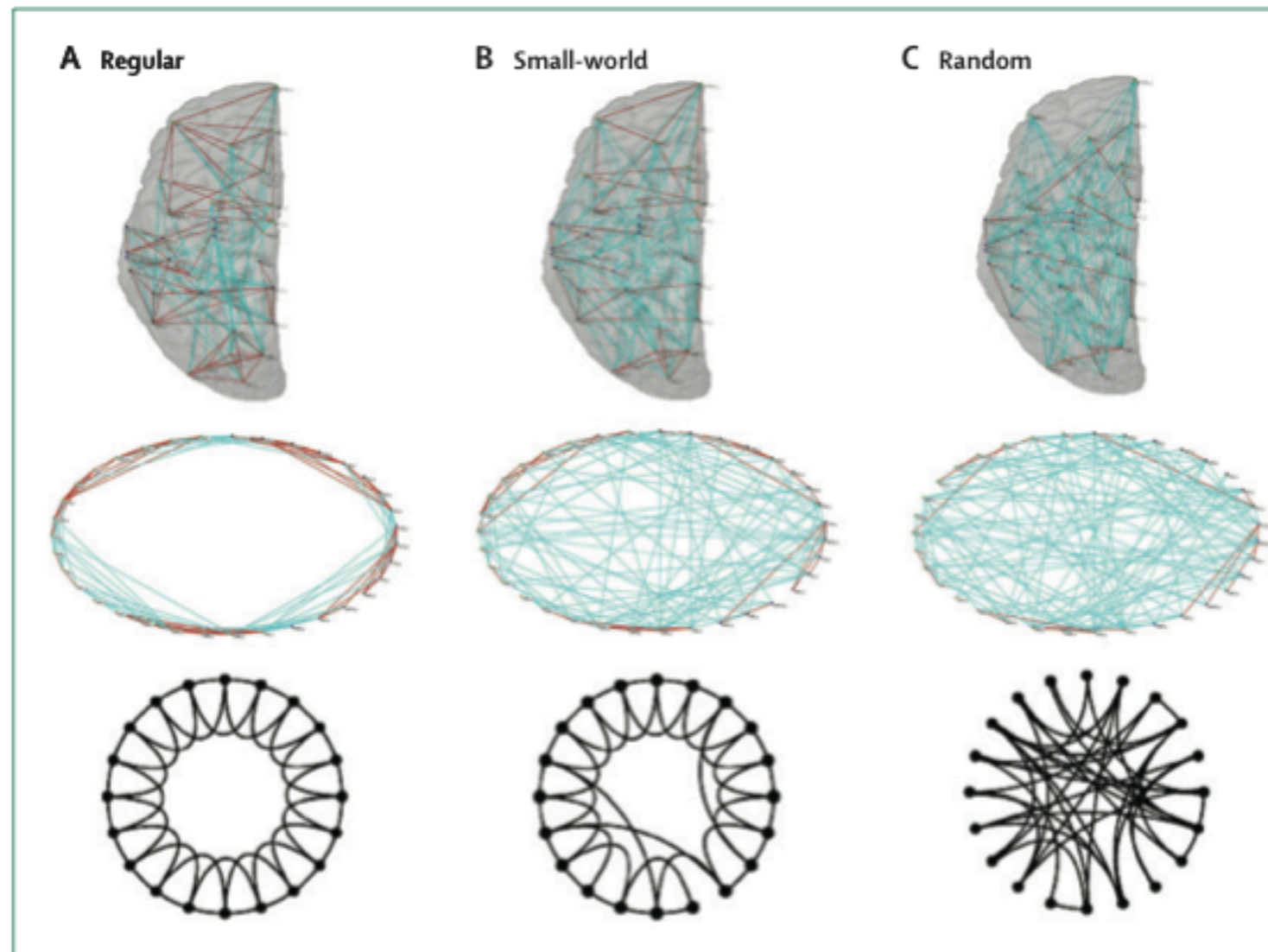
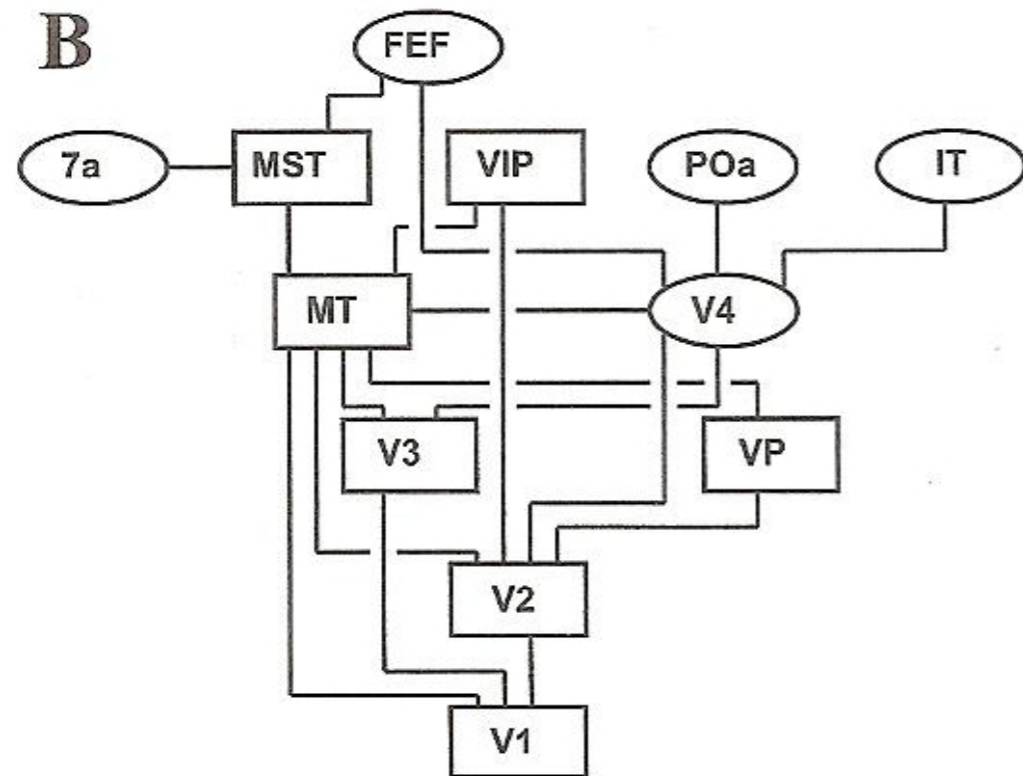
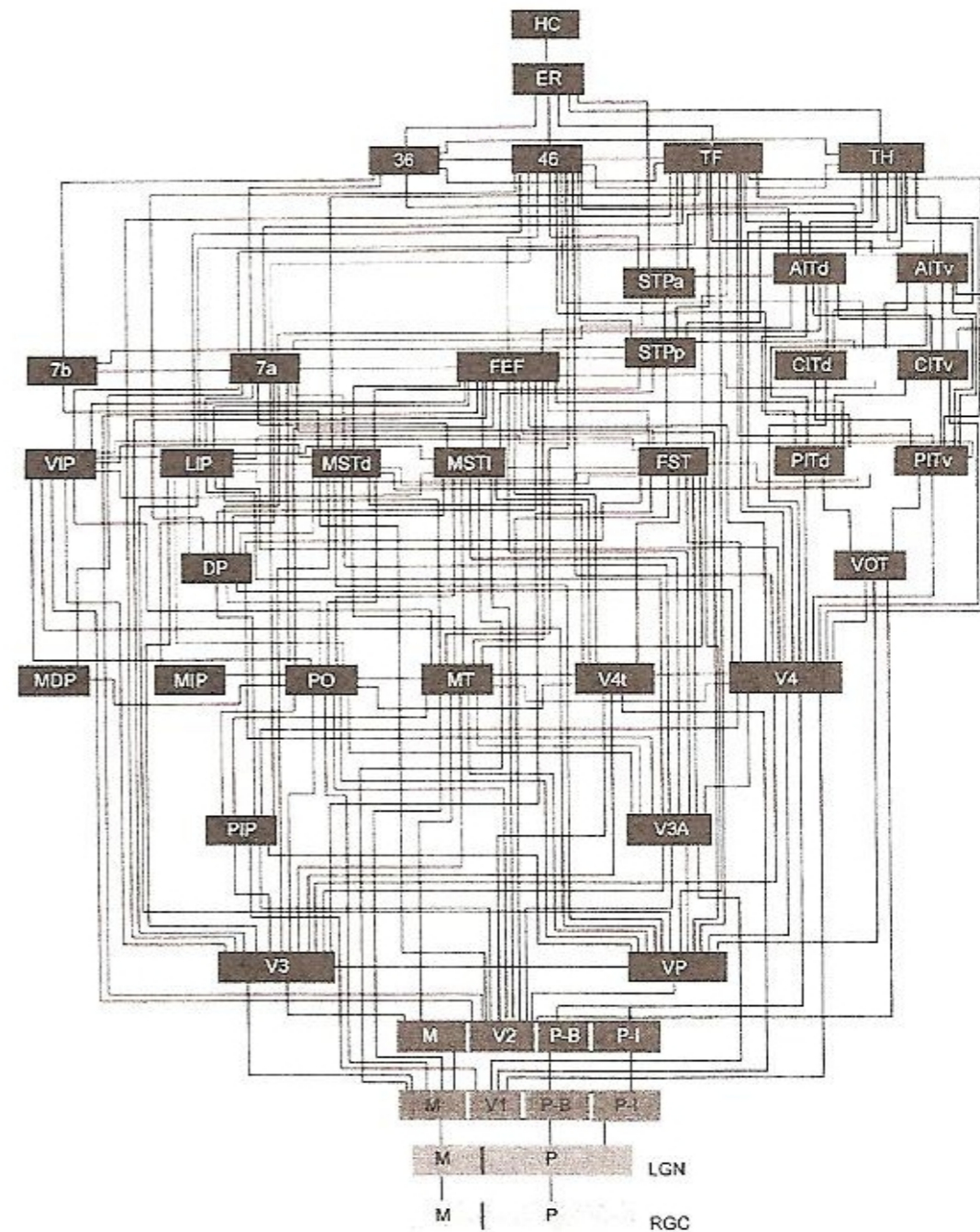
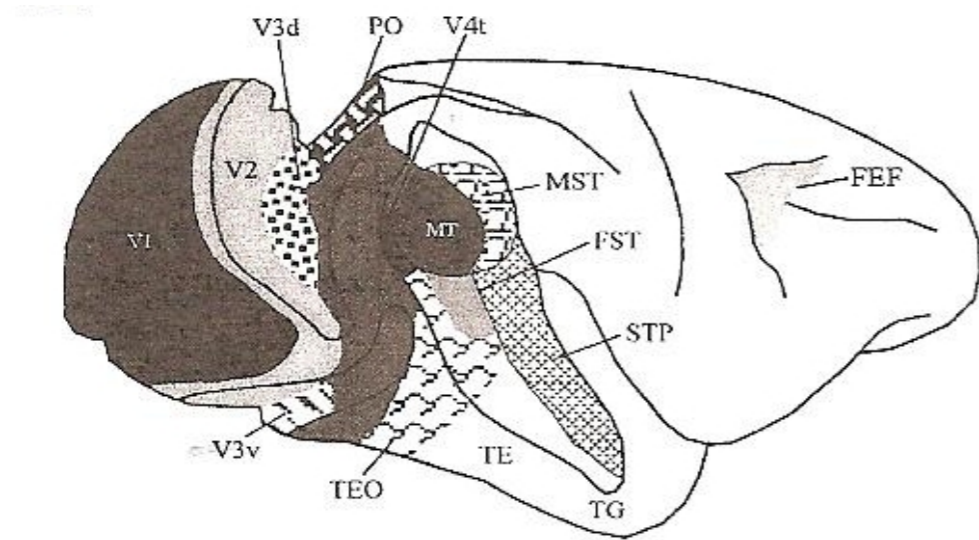
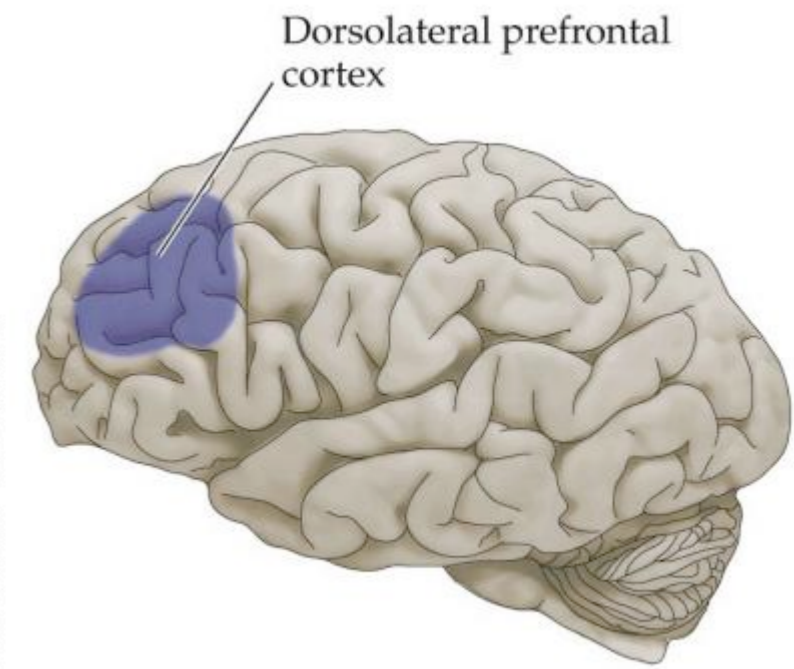
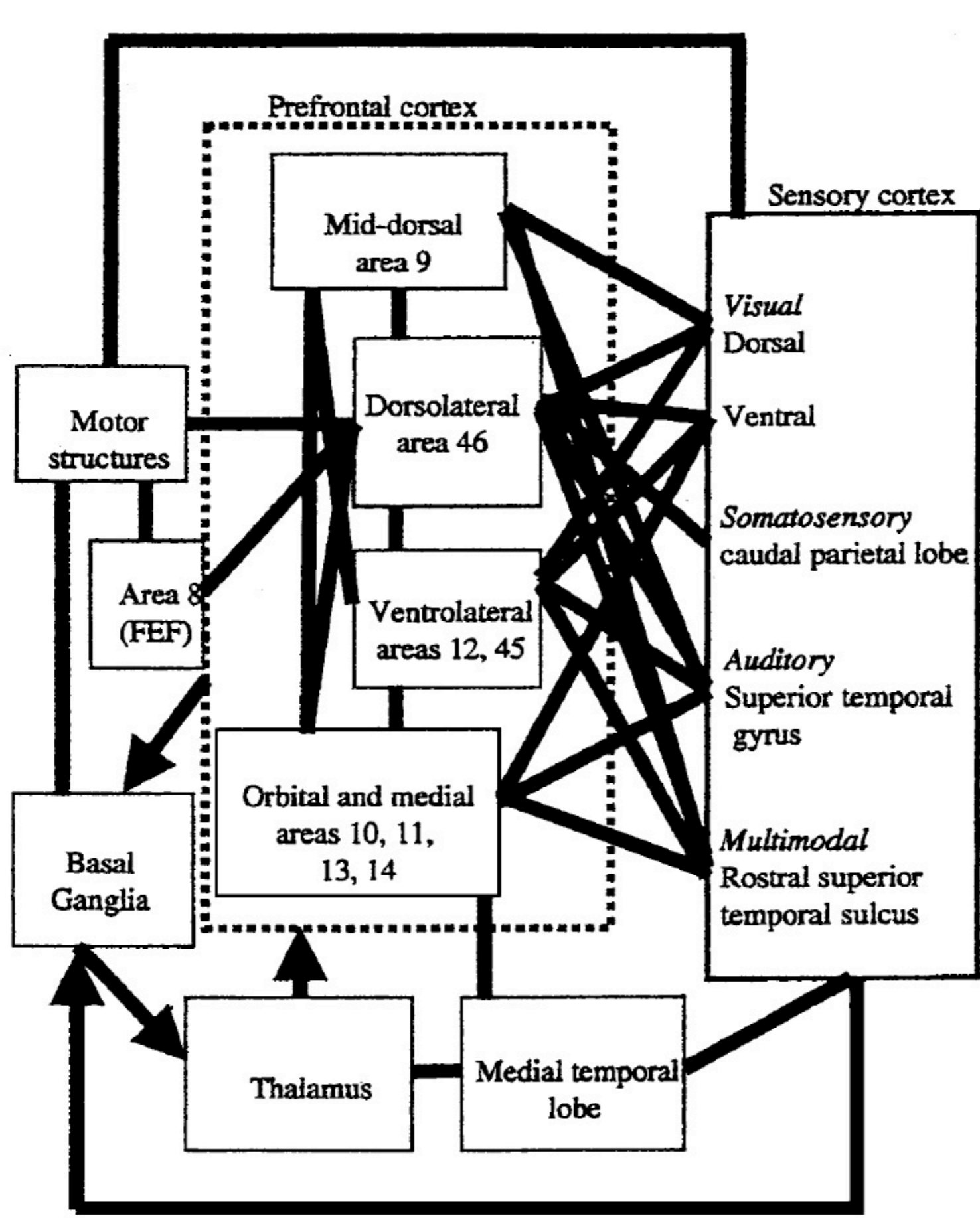


Figure 5: Schematic representation of a small-world brain functional network and of simulated regular and random networks with 35 nodes and 120 connections

Regular networks (A) have many connections between neighbouring regions (red lines) and few connections with distant nodes (light blue lines). Small-world networks (B) have fewer local connections and more long-distance connections. Random networks (C) have few local connections and many connections between distant regions. Each network is shown overlaid onto a standard template (top row) and in schematic representation (middle row). Nodes represent 35 cortical points of the left hemisphere drawn from the automated anatomical labelling template, and edges represent functionally connected nodes. The real-world network was extracted from a single person, the corresponding regular (A) and random (C) networks were simulated with the Brain Connectivity Toolbox.⁸⁹ The corresponding theoretical Watts–Strogatz network models are also shown (bottom row). Adapted from Watts and Strogatz³⁸ by permission of Macmillan Publishers Ltd.

Conectividad de la corteza visual





Conectividad funcional

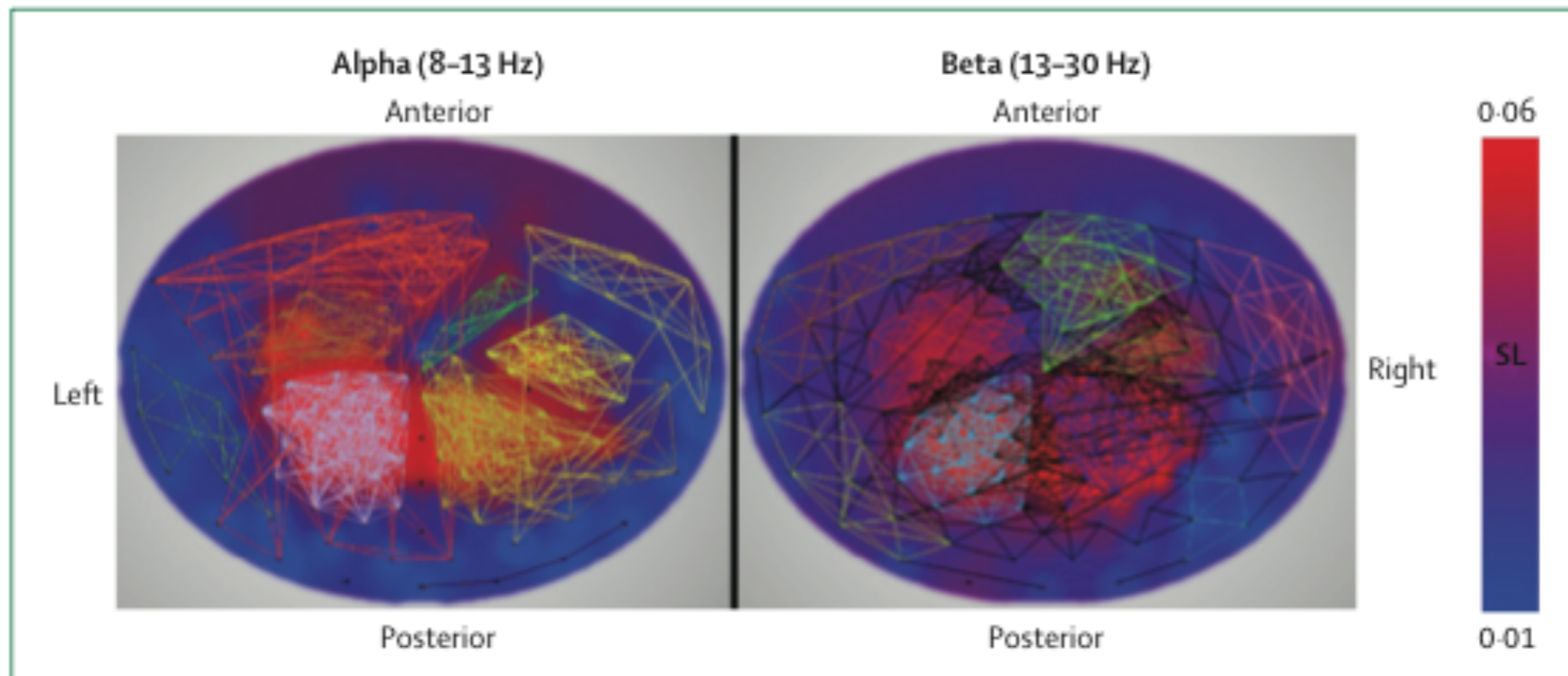


Figure 3: Functional connectivity on resting-state MEG in healthy people

Headplot showing functional MEG network of a healthy woman aged 63 years in the alpha (8–13 Hz) and beta (13–30 Hz) frequency ranges.¹³ Coloured lines show different functional subnetworks (modules), black lines represent their interconnections (only shown in beta-band example). Background colours show connectivity strength (red are hub—ie, highly connected—regions). MEG=magnetoencephalography. SL=synchronisation likelihood.¹³

La diferencia de potencial genera una corriente extracelular que se propaga en el espacio, según el principio de “la fuente y el resumidero”, y que es la base de la conducción volumétrica en el tejido cerebral.

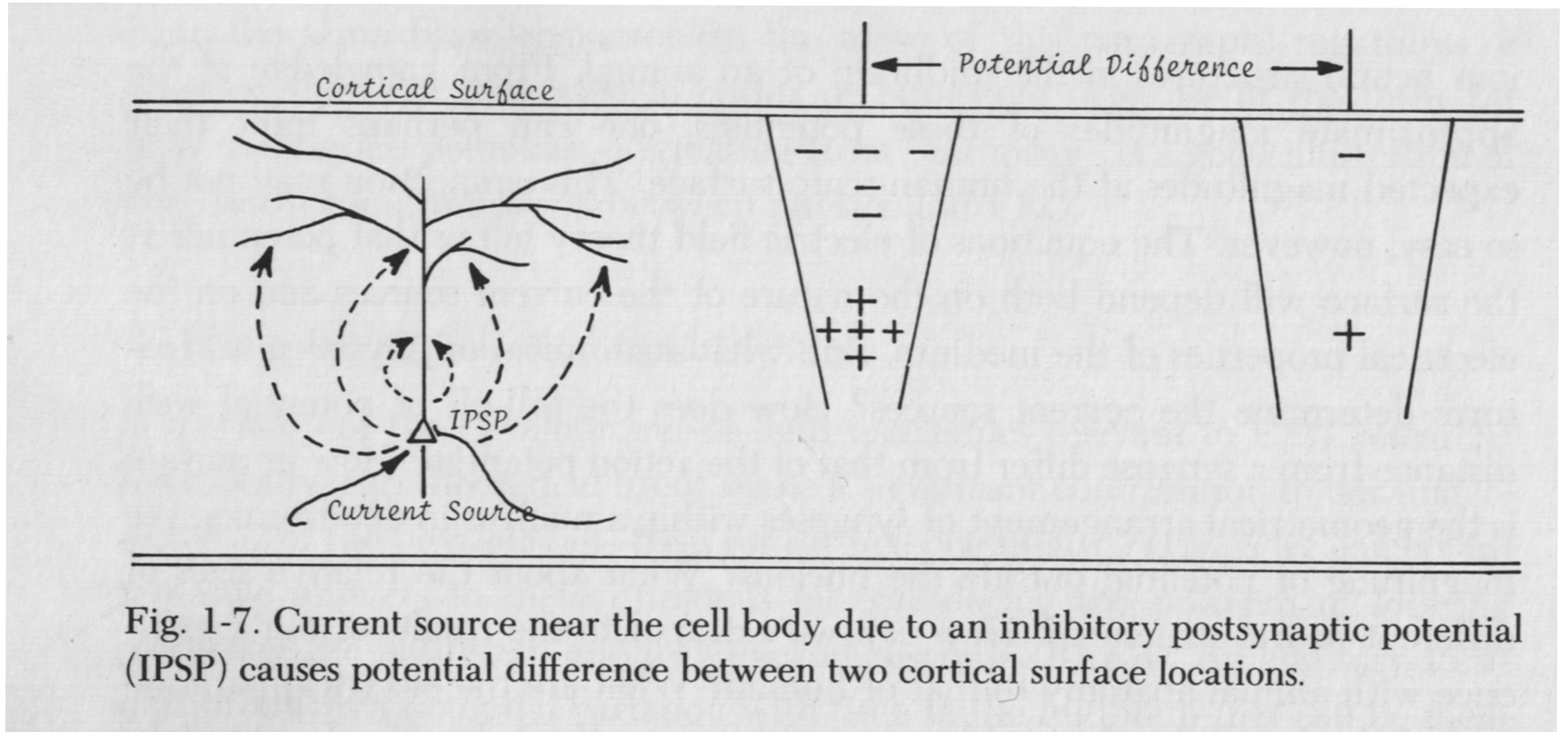


Fig. 1-7. Current source near the cell body due to an inhibitory postsynaptic potential (IPSP) causes potential difference between two cortical surface locations.

La configuración eléctrica que predomina en la corteza corresponde a un dipolo de capa

Medición del Potencial eléctrico: aplicación del concepto del ángulo sólido.

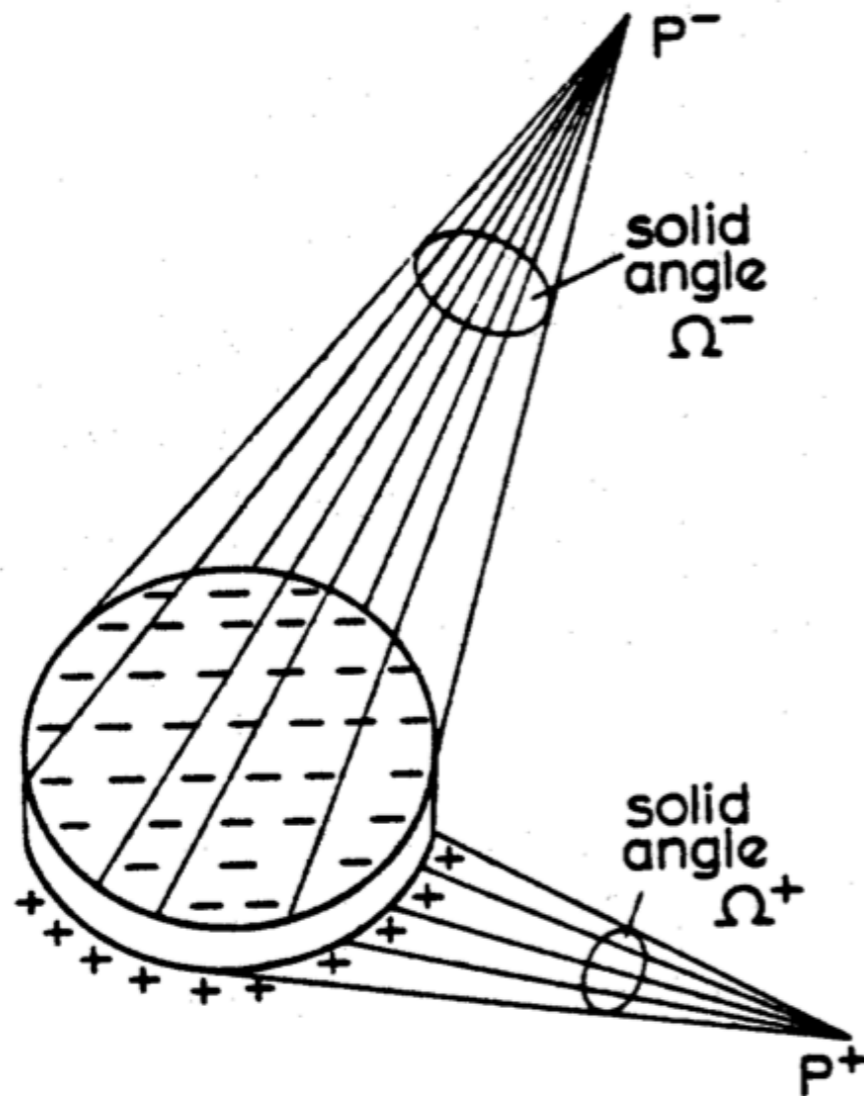


FIG. 2. Schematic representation of the solid angle principle of volume construction: in an infinite homogeneous medium the potential measured at point P^- is proportional to the solid angle Ω^- subtended at P^- by the negative, or at point P^+ to the solid angle Ω^+ subtended at P^+ by the positive surface of the disk-shaped dipole layer. At all points facing the negative side of the dipole layer, the sign of the potential is negative, and at all points facing its positive side, it is positive.

Medición del Potencial eléctrico: aplicación del concepto del ángulo sólido.

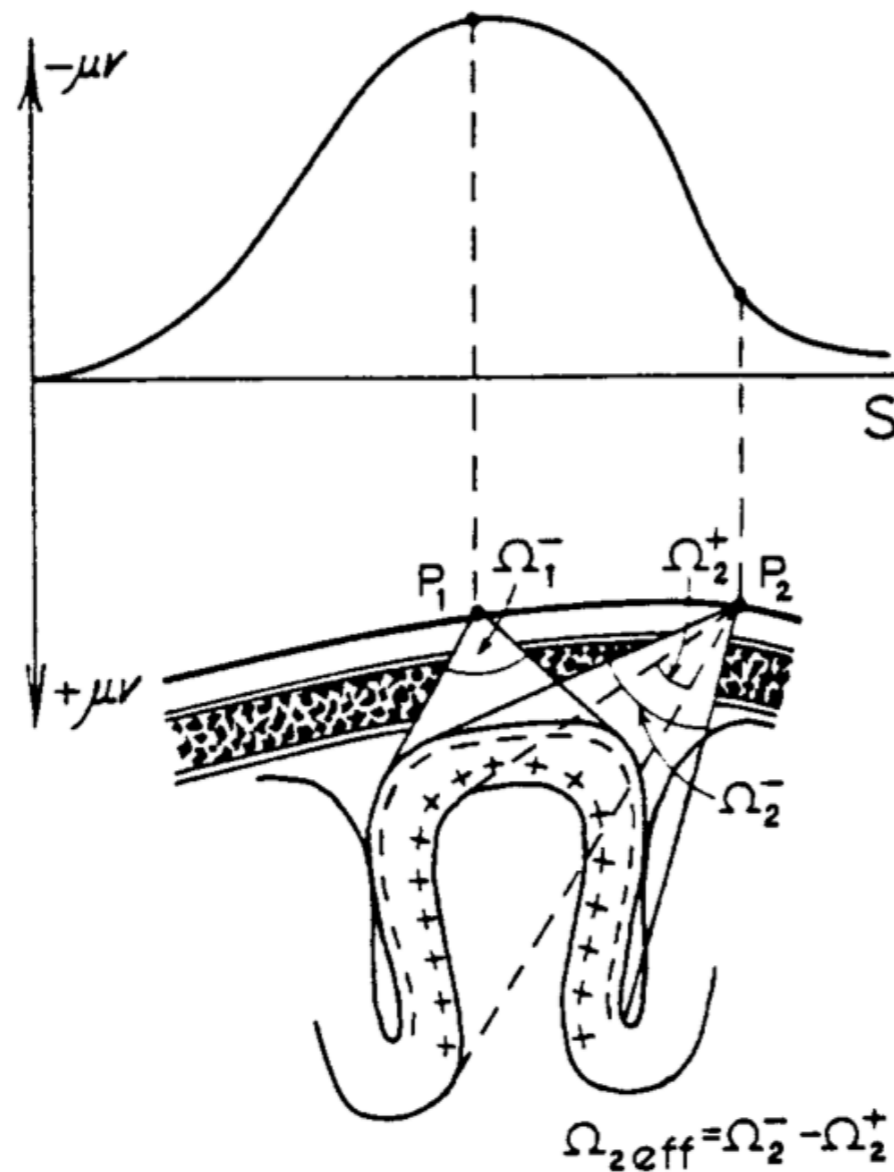
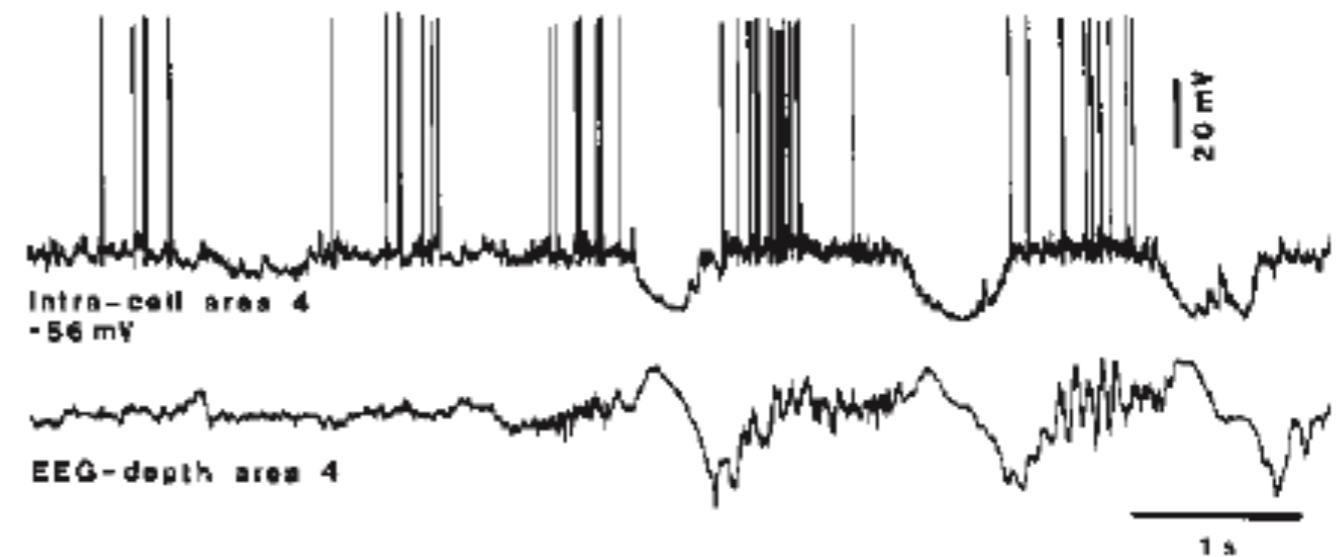
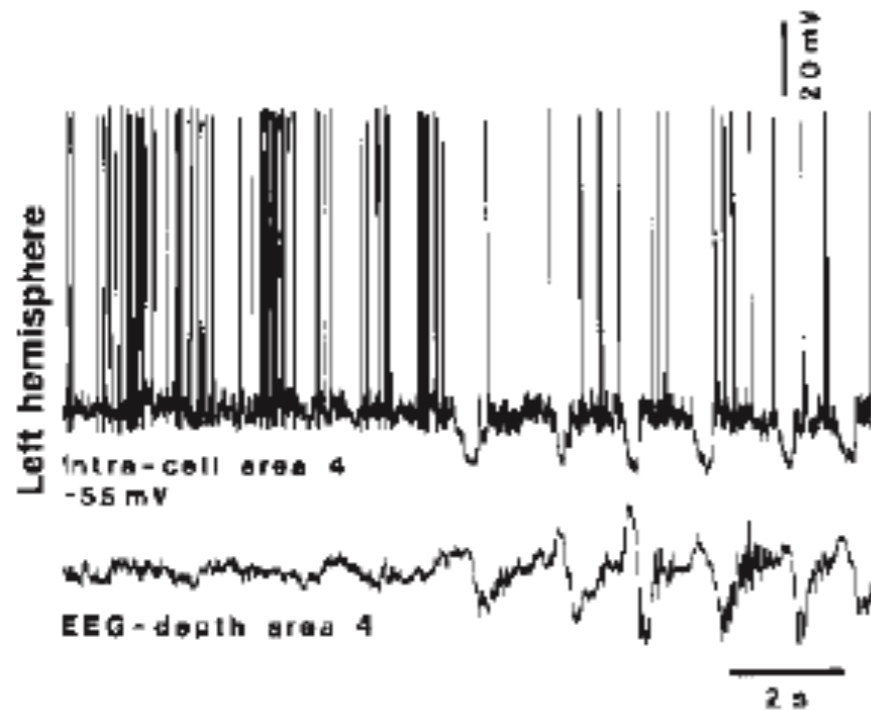
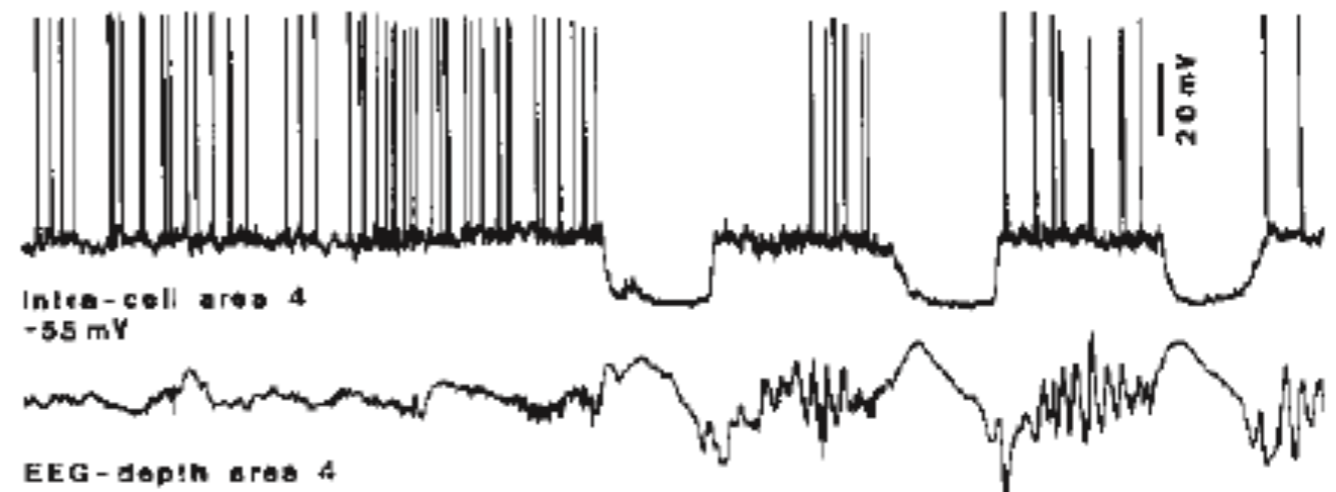
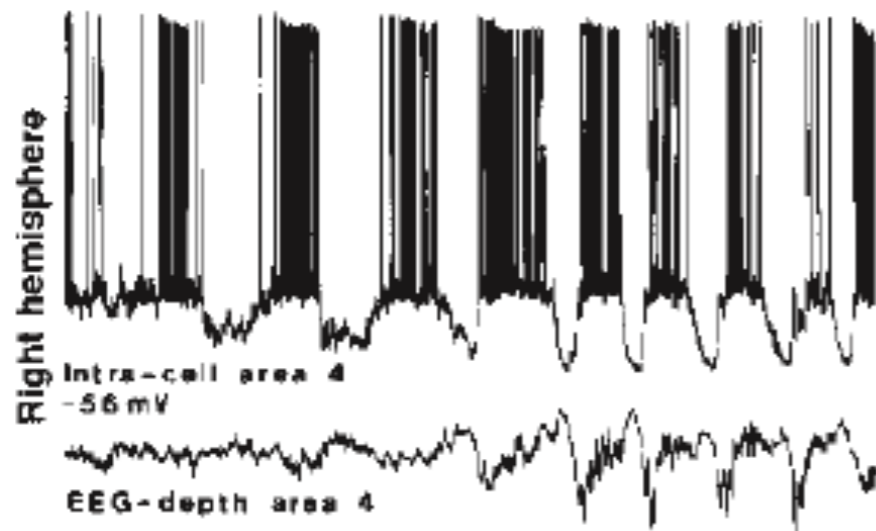


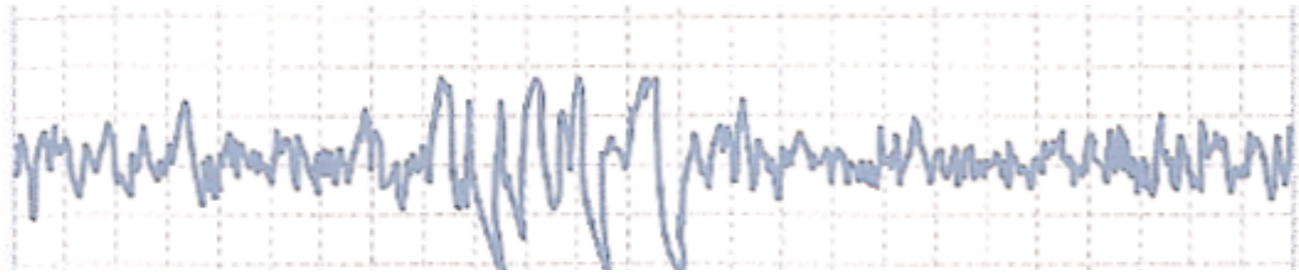
FIG. 7. Potential distribution along line S on the scalp created by the synchronous activation of a curved portion of cortex that occupies the crown of a gyrus and its two sides forming the proximal walls of the two adjacent sulci. At P1, the potential depends only on the solid angle Ω_1^- , since at this point an electrode "sees" only a portion of the negative side of the dipole layer. At P2, an electrode "sees" the negative side of the portion of the dipole layer occupying the crown of the gyrus and the wall of the proximal sulcus under the angle Ω_2^- ; however, it also "sees" under the smaller angle Ω_2^+ the positive side of the portion of the dipole layer located in the wall of the distal sulcus. The potential at P2 is therefore smaller than would be expected if only Ω_2^- were the angle determining the size of the potential at P2 and is proportional to the effective solid angle Ω_{eff} which equals the difference between Ω_2^- and Ω_2^+ , the polarity being negative, since $\Omega_2^- > \Omega_2^+$. As is the case for a flat area of cortex oriented in parallel to the scalp the potential profile is bell-shaped. (Taken in part from Gloor, 1975.)

Registro de EEG

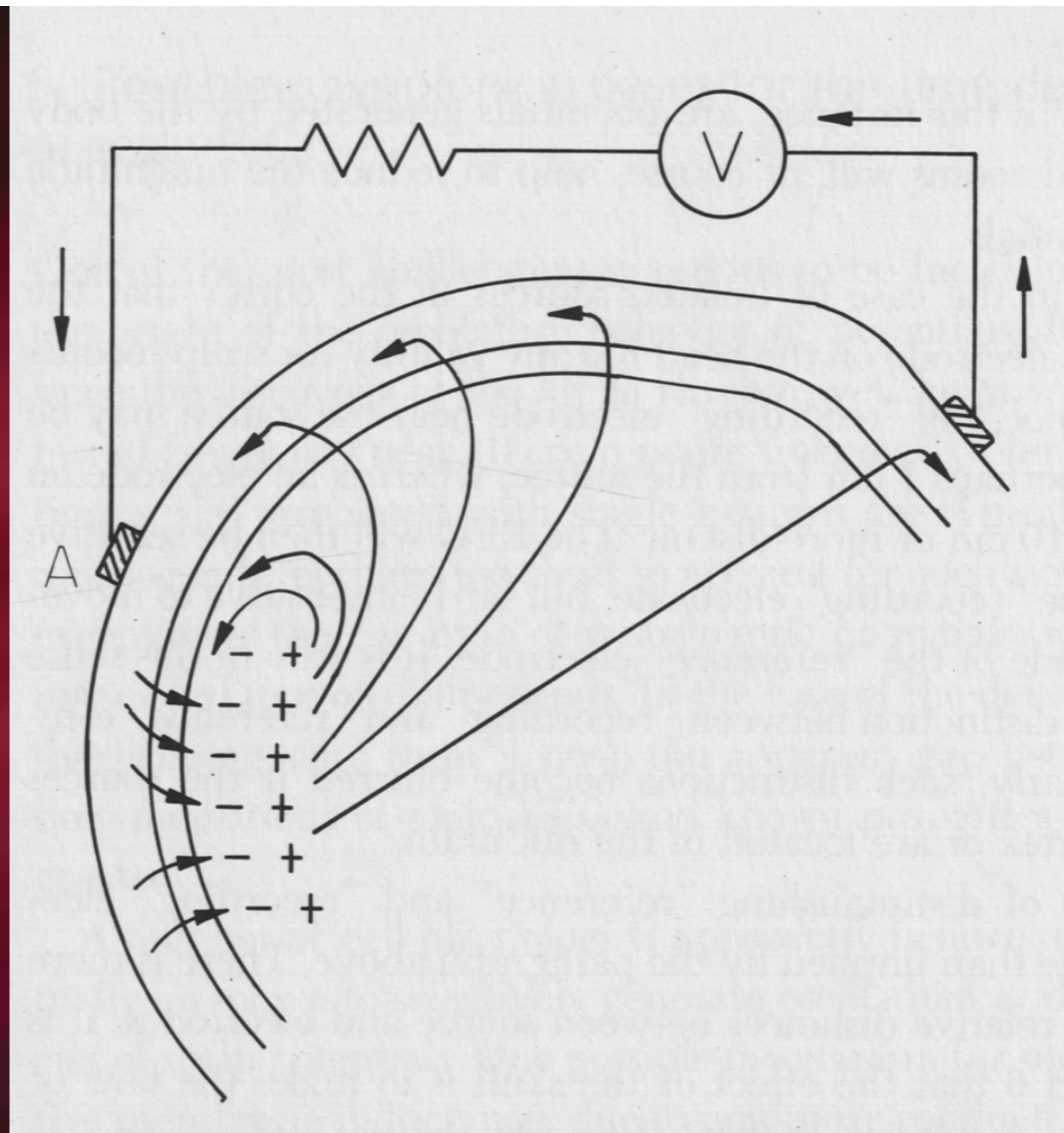


El EEG representa la suma del potencial de membrana de neuronas sincrónicamente oscilantes





$$\Phi(\vec{r}) = \frac{1}{4\pi\epsilon_0} \sum_{i=1}^n \frac{q_i}{R_i}$$

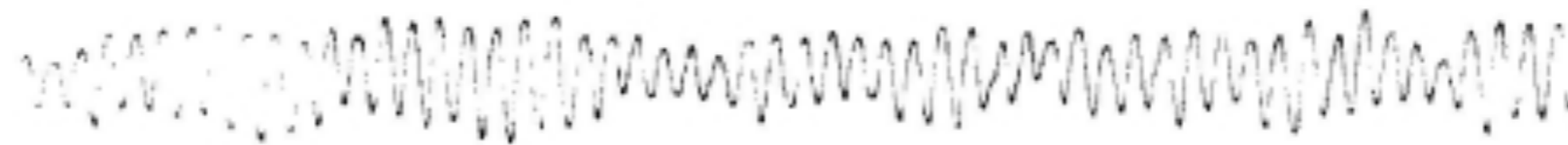


Existen distintas bandas de frecuencia

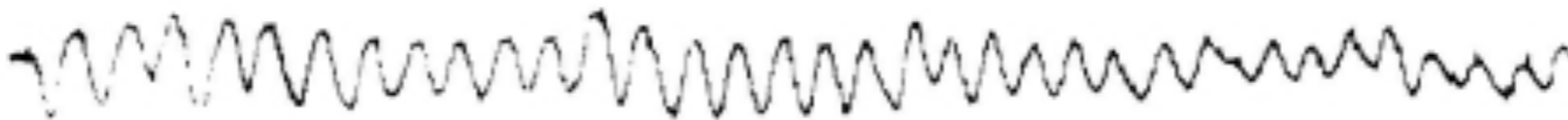
Beta > 13 Hz



Alpha 8-13 Hz



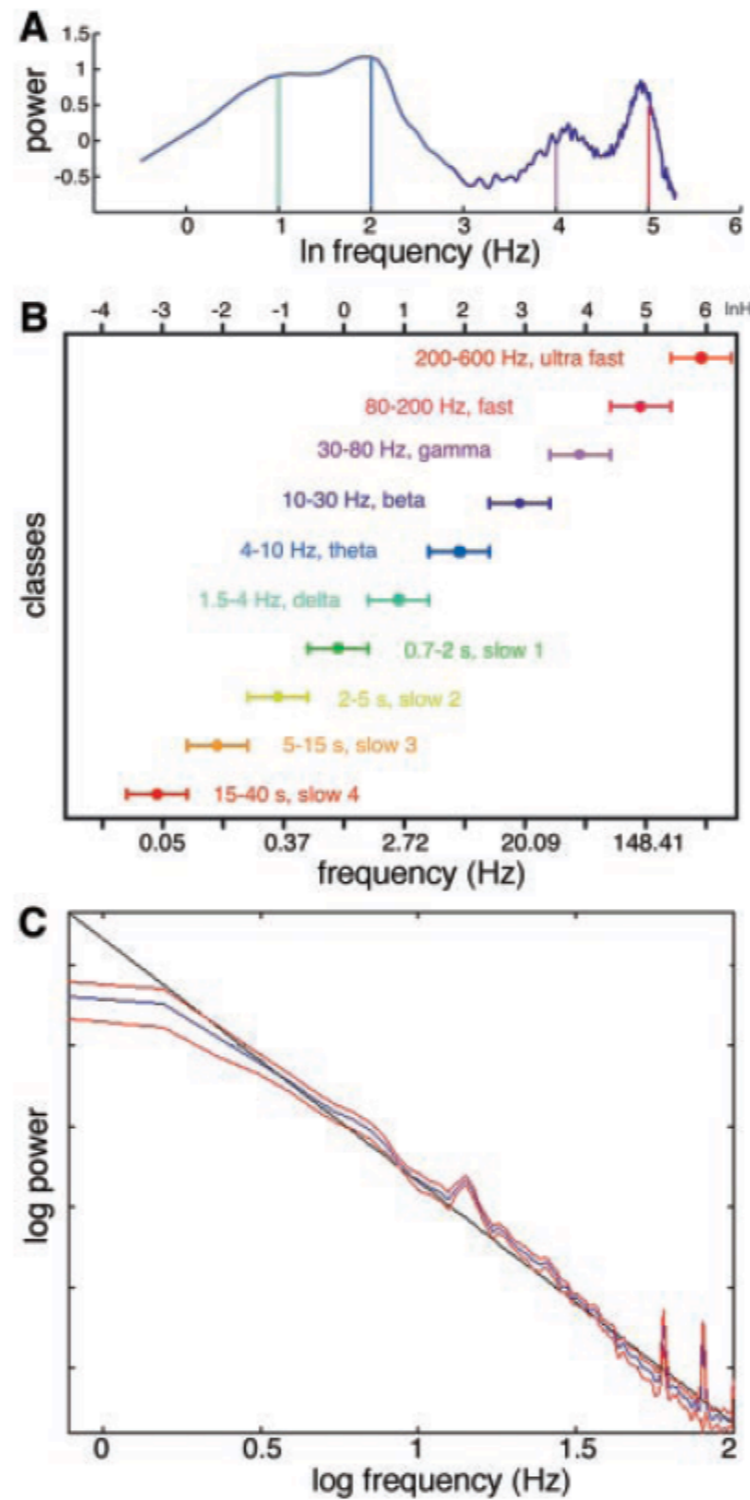
Theta 4-7 Hz



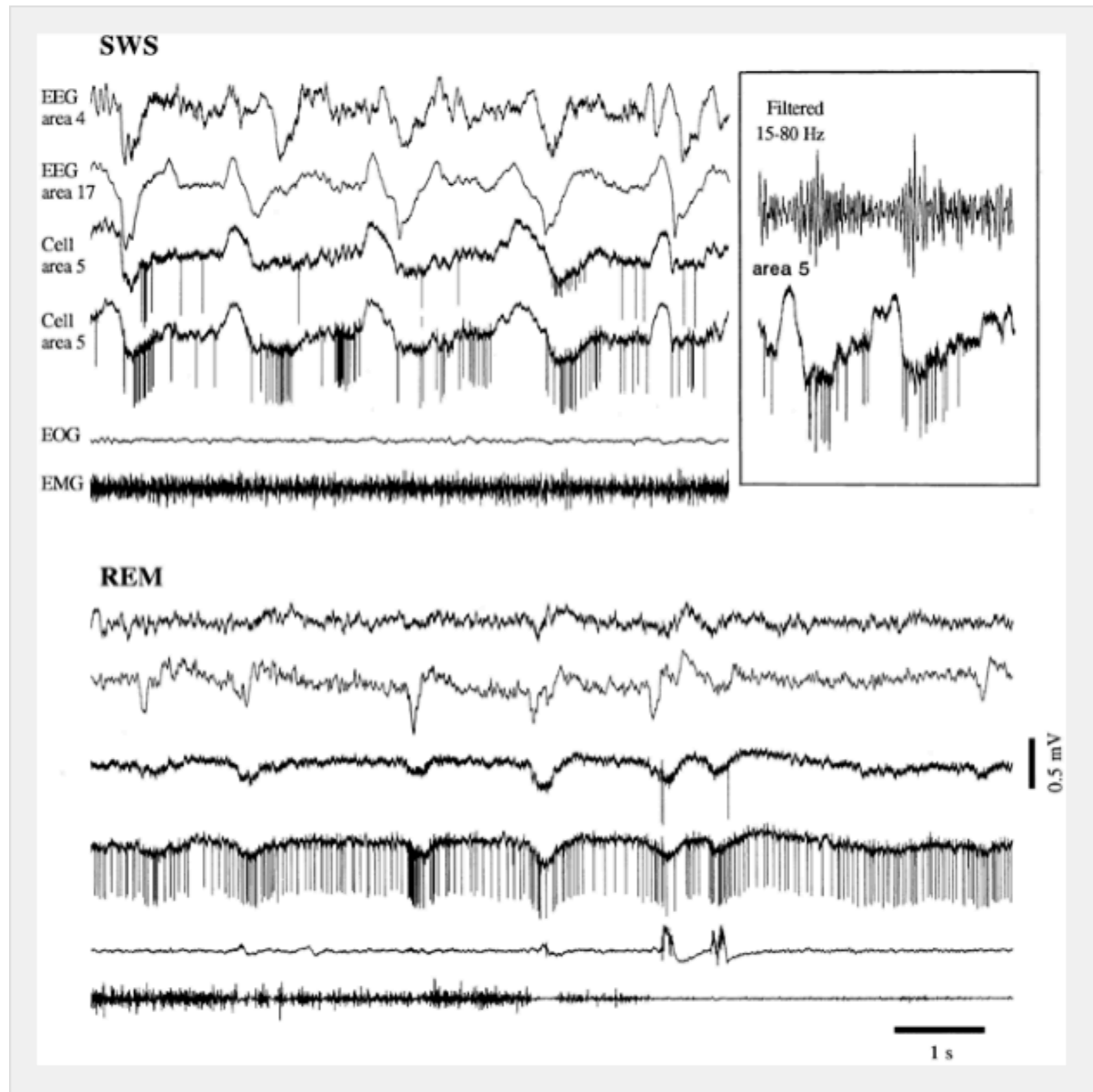
Delta < 4 Hz



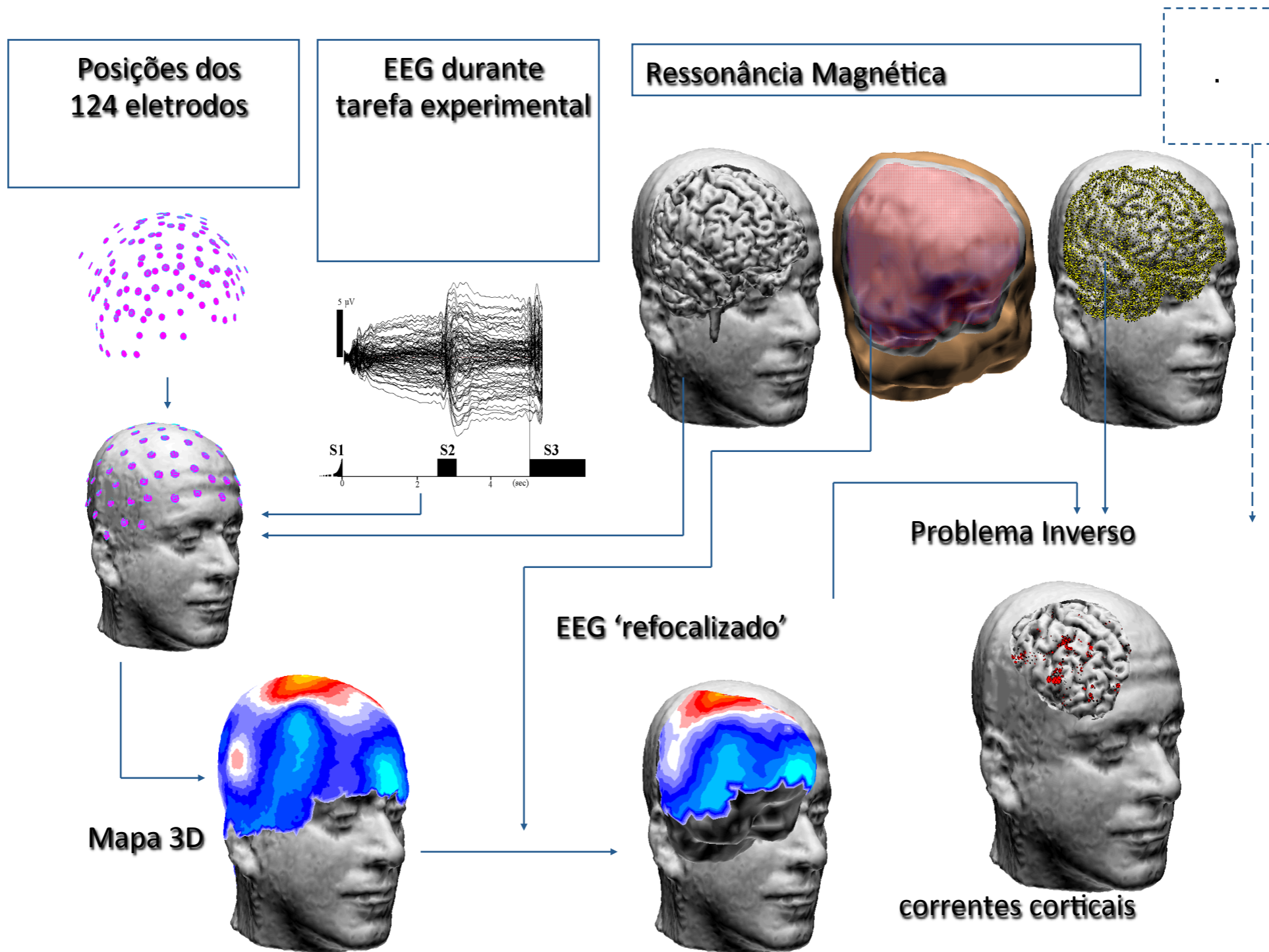
Escala temporal de los ritmos cerebrales



Los ritmos cerebrales definen macroscópicamente el estado cerebral

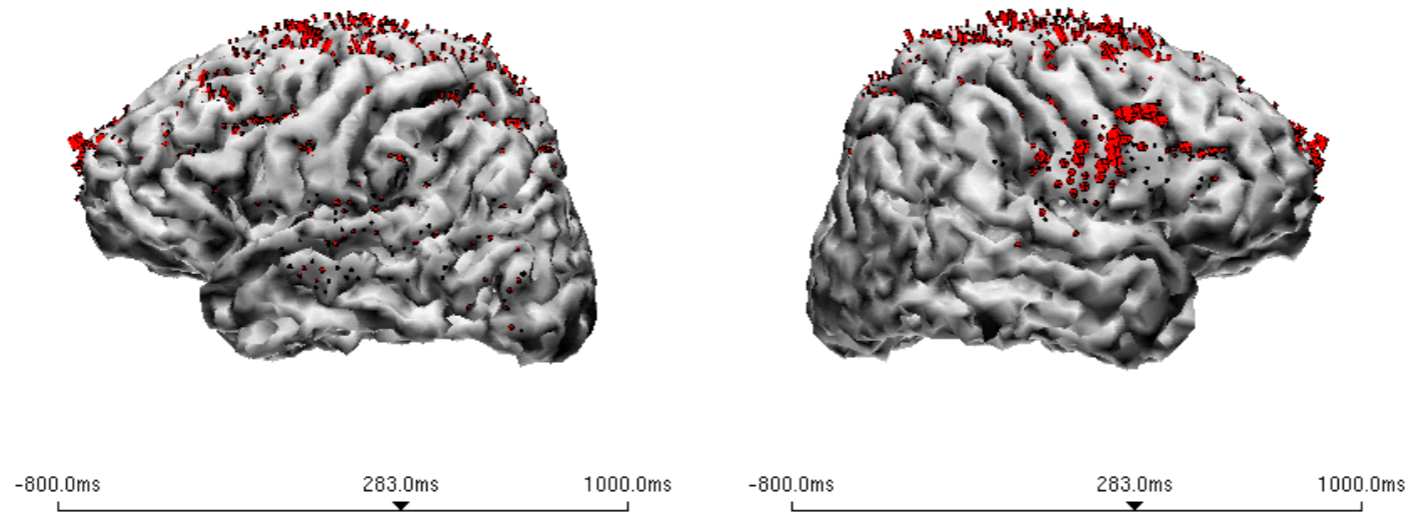


Análisis de fuente

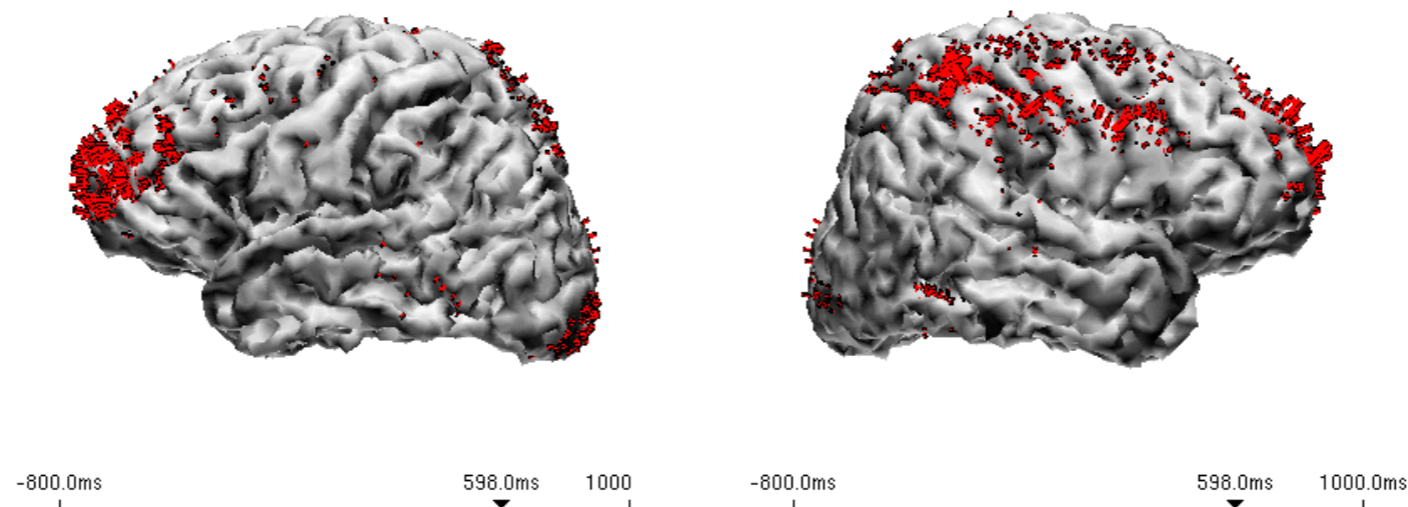


Reconstrucción de generadores de corrientes corticales

A)



B)



Análisis del EEG en el dominio del tiempo y la frecuencia

PARADIGMA EXPERIMENTAL



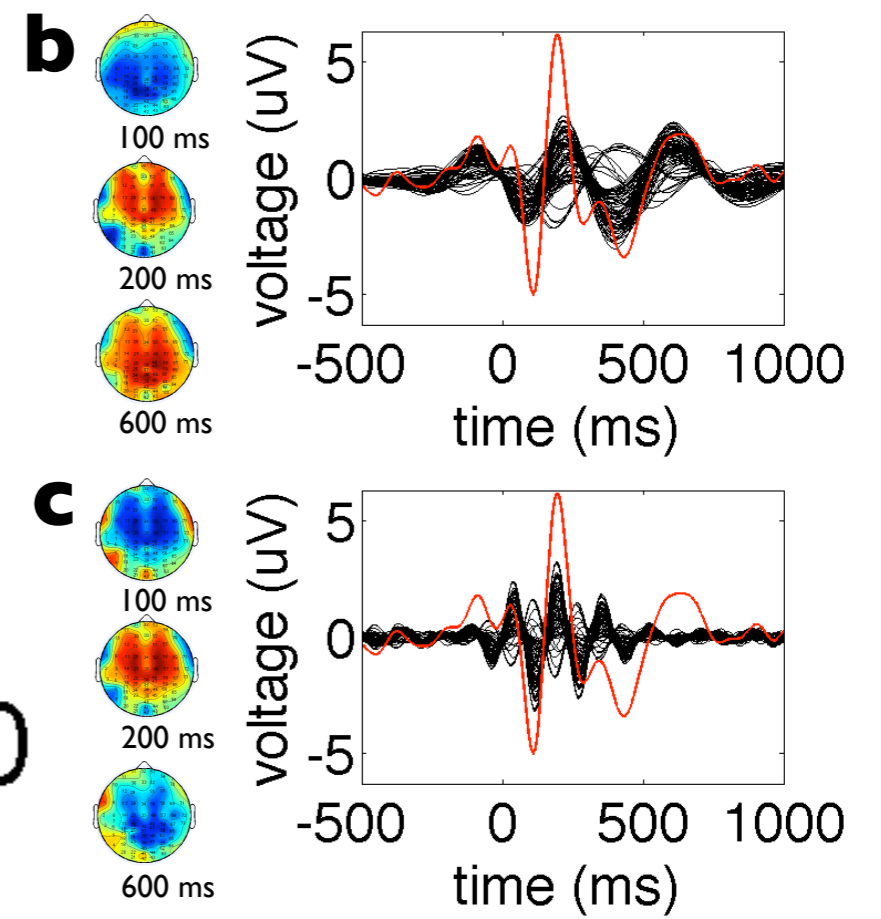
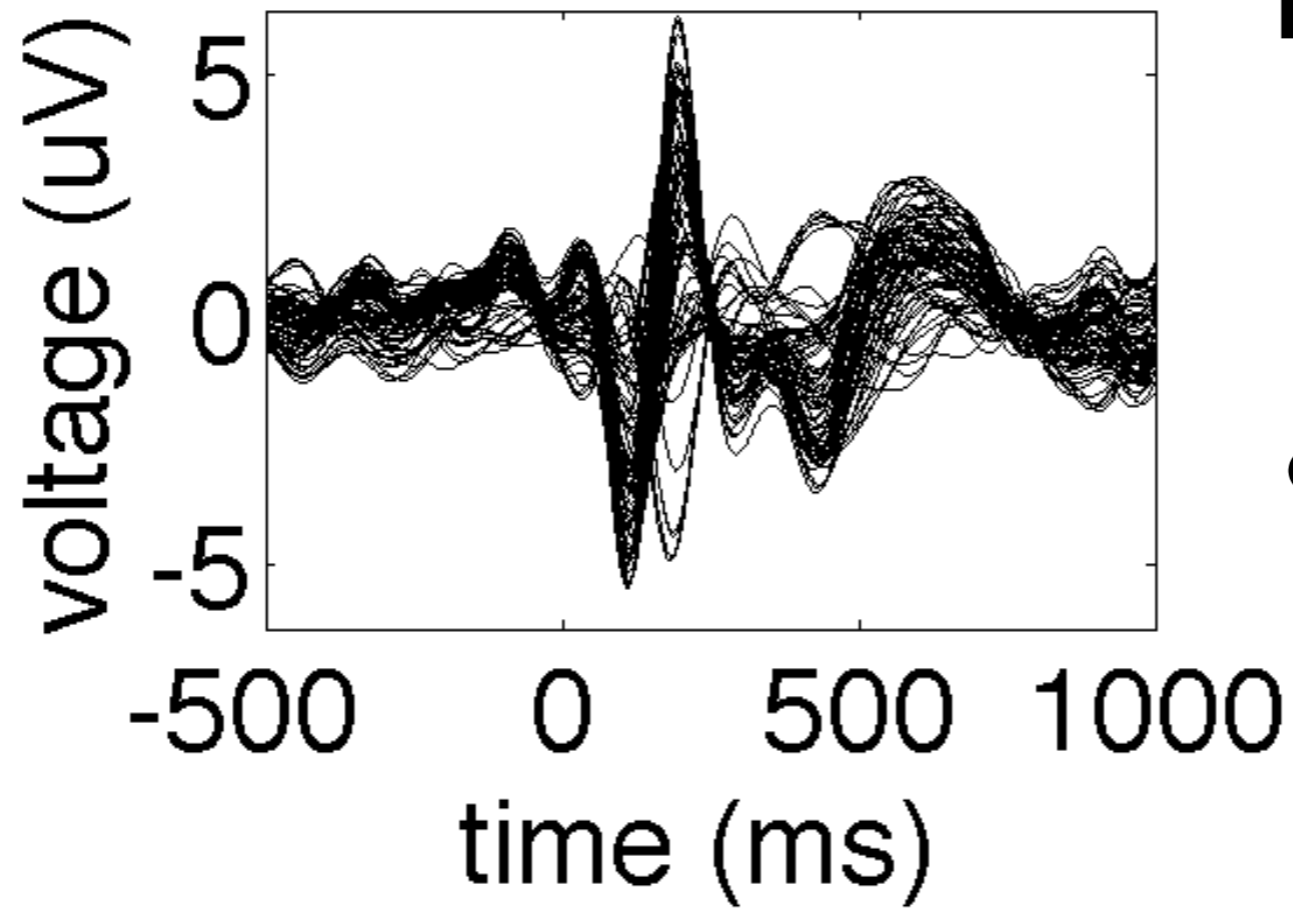
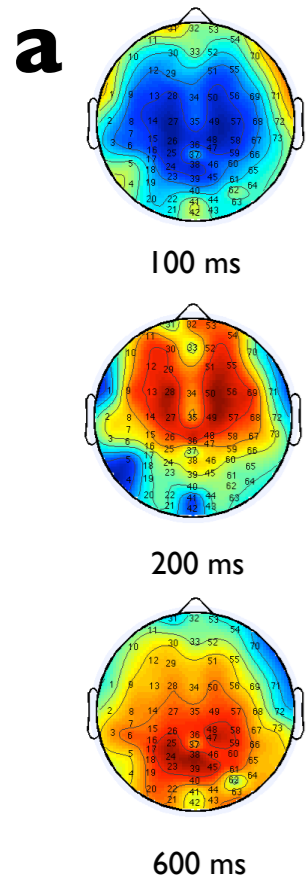
CASA

LOBO

TONO

TAME

- Estructura consonante-vocal consonante-vocal.
- 500 ms de duración promedio.
- Asincronía entre inicio de estímulos entre 1.7 y 2.3 seg.

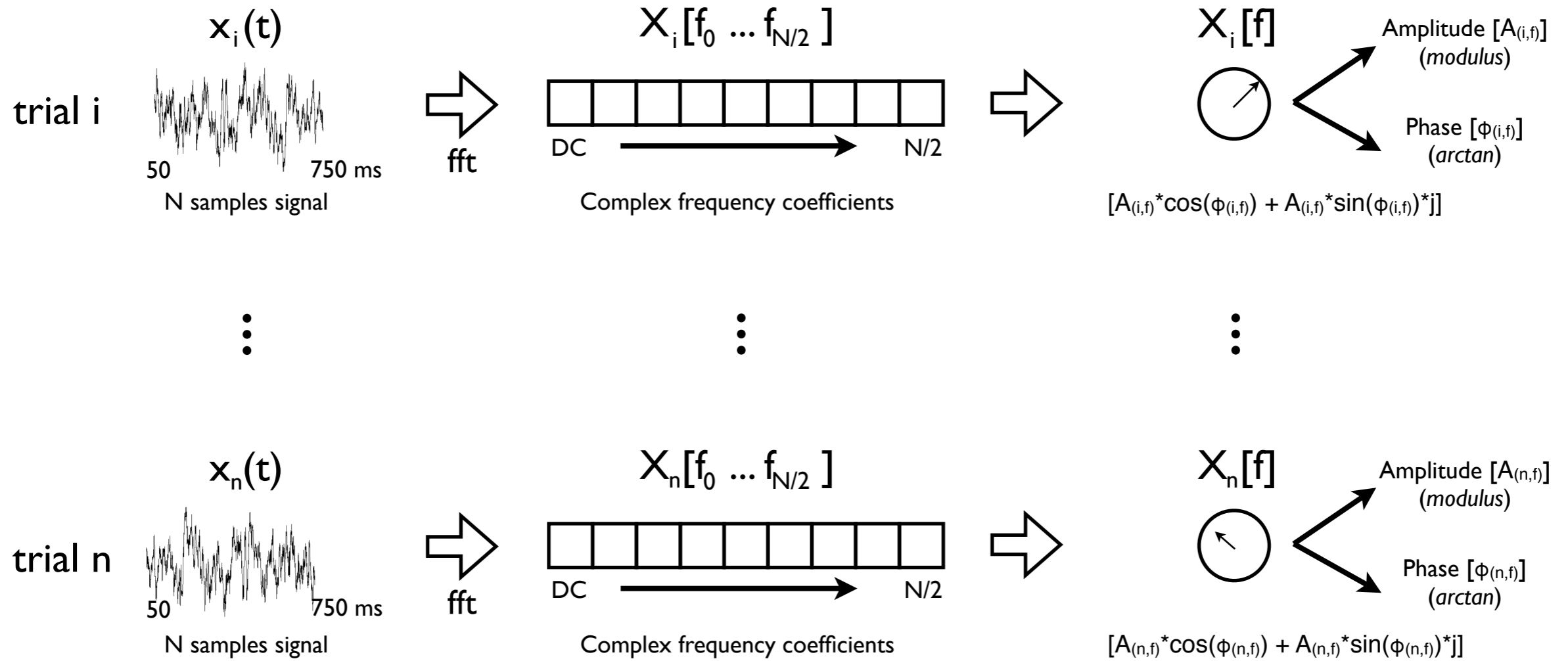


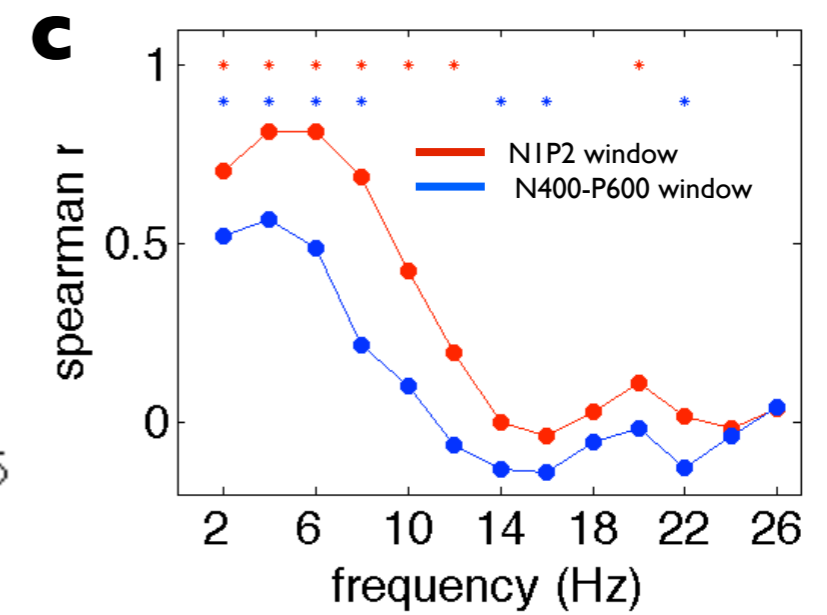
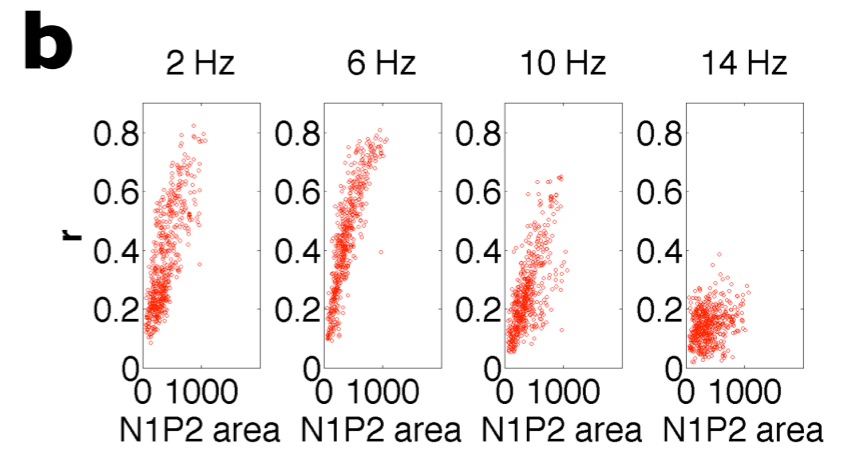
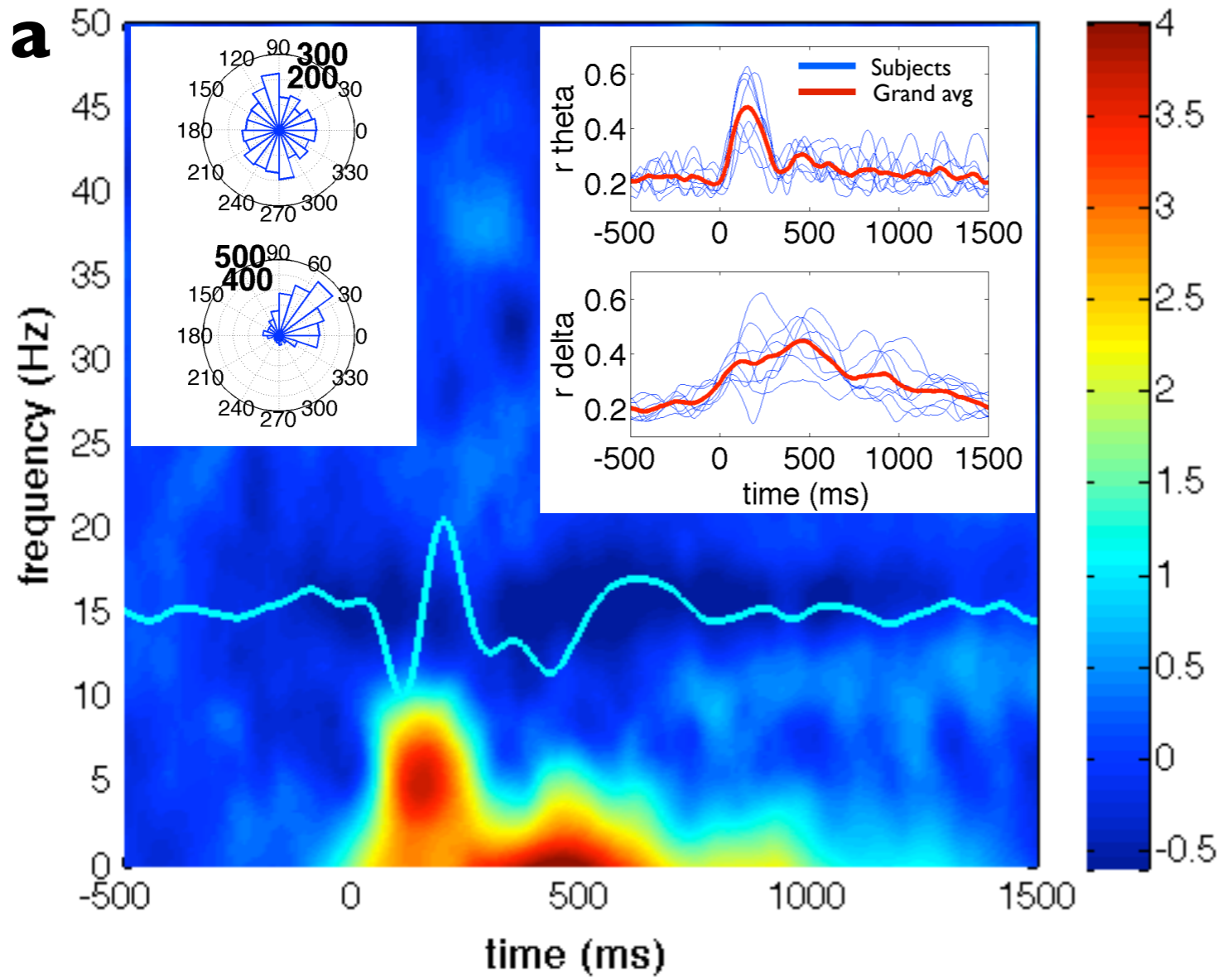
A)

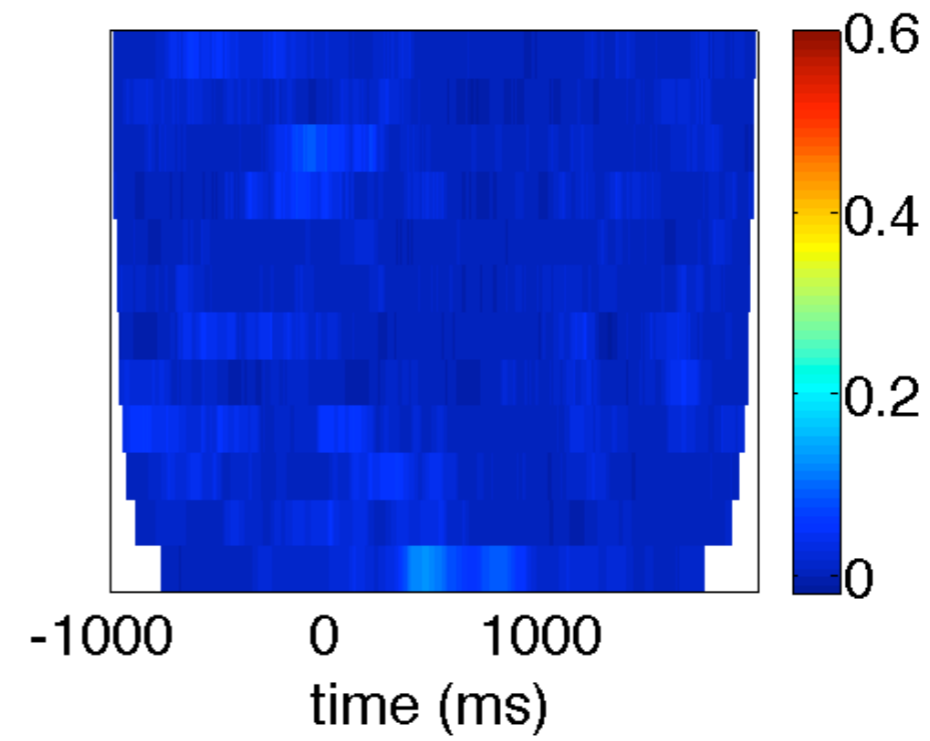
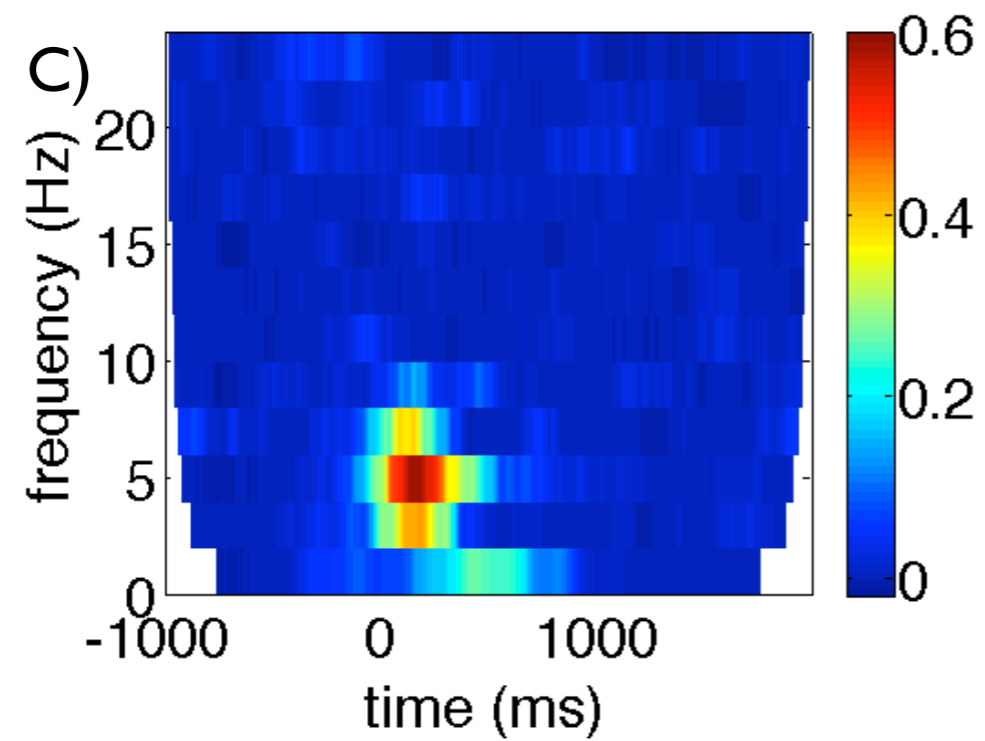
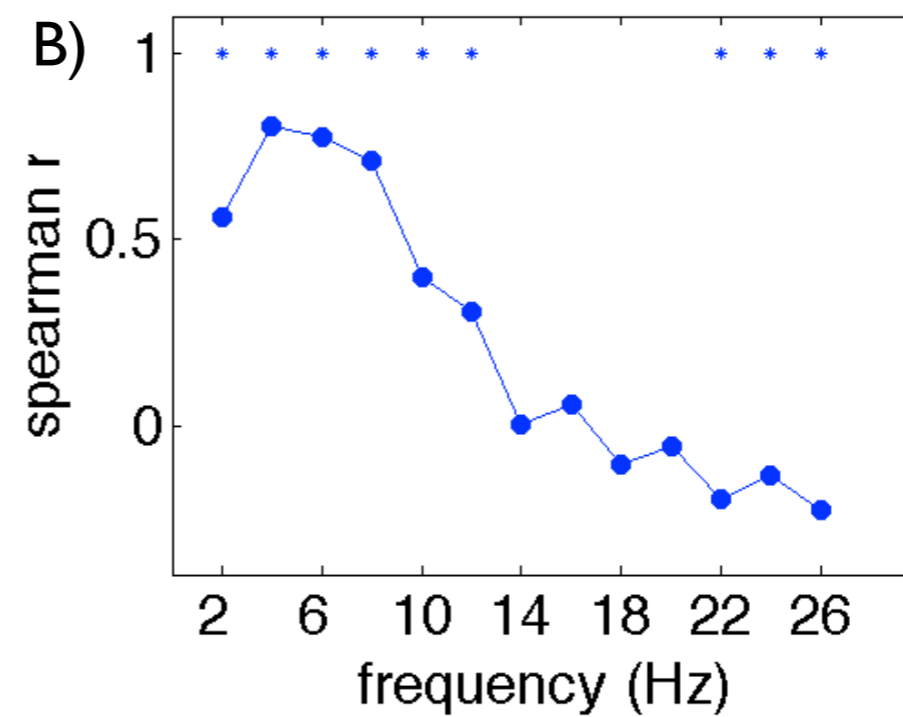
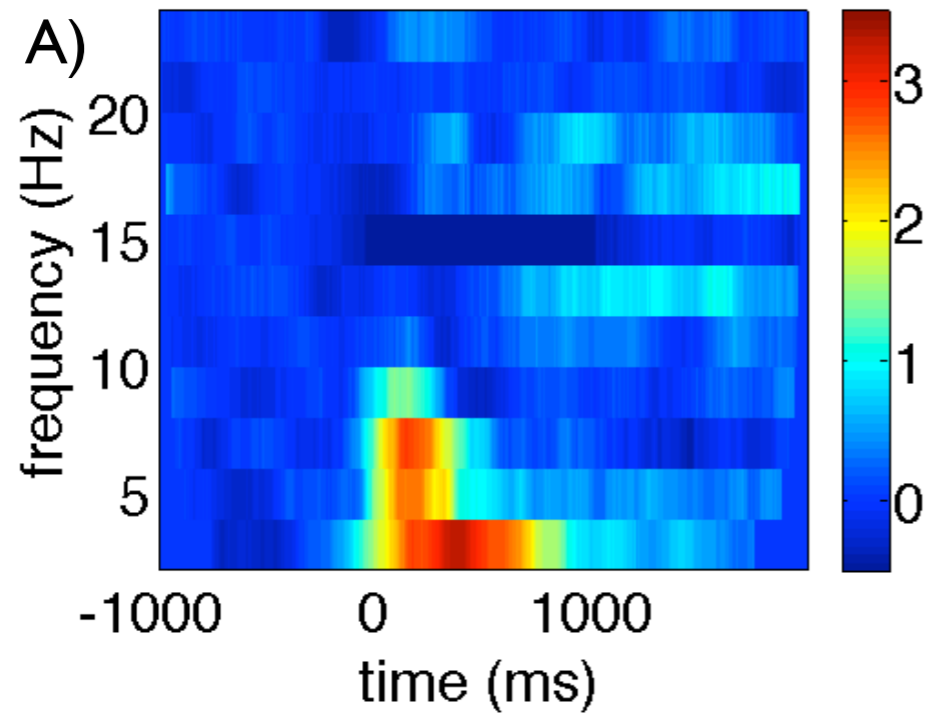
Time domain signal

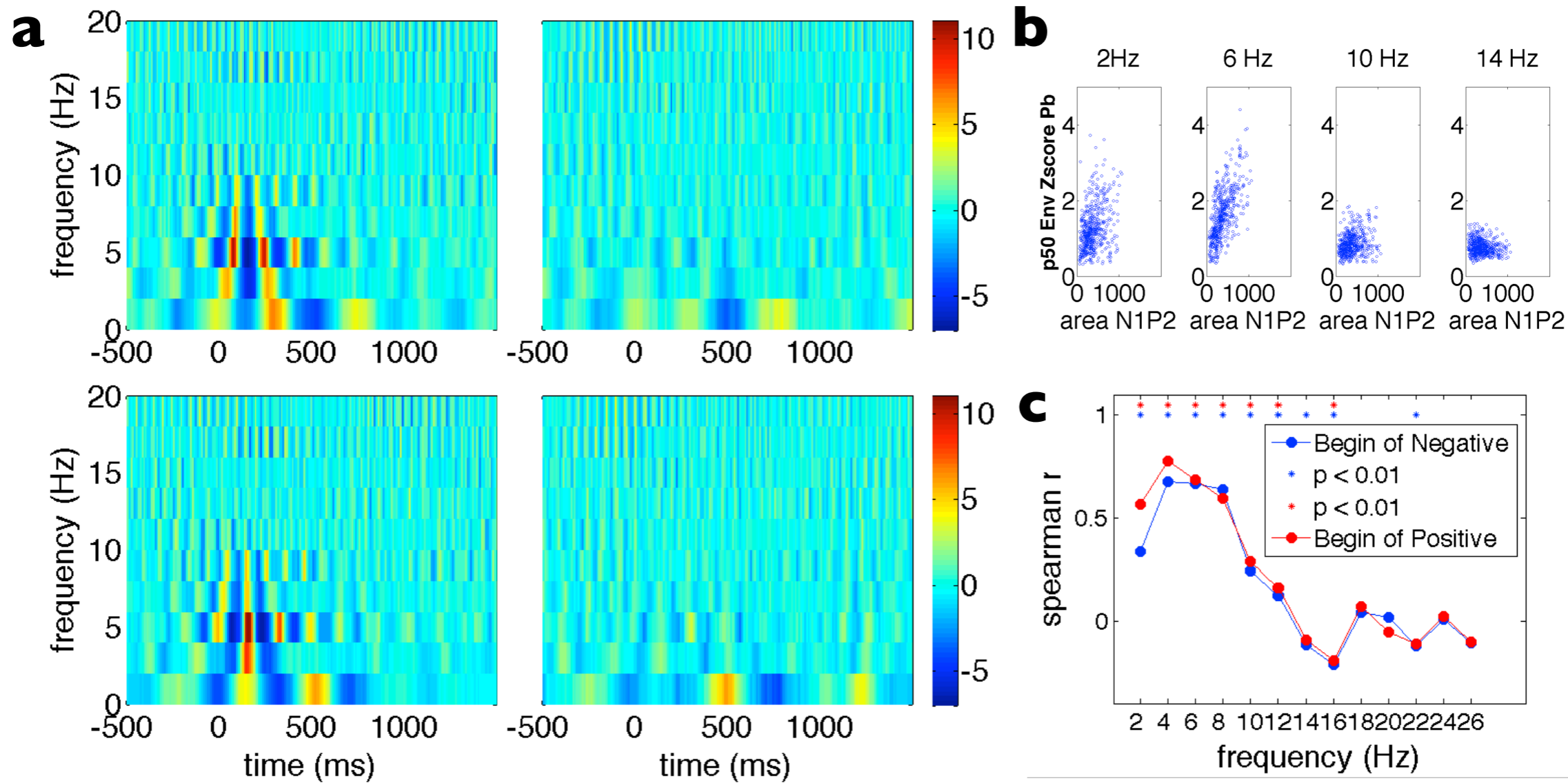
Frequency domain signal

Each frequency coefficient



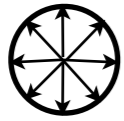






B)

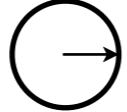
Generation of circular uniform random distribution of numbers

 $X[f]$


n' scalars (n trials)



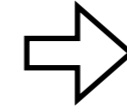
Replacement of each phase value in the original complex coefficients

 $X_i[f]$


...

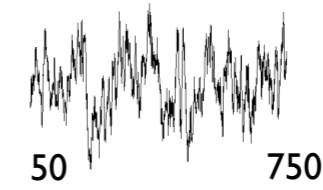
 $X_n[f]$


$[A_{(n,f)} \cdot \cos(\phi_{(n',f)}) + A_{(n,f)} \cdot \sin(\phi_{(n',f)}) \cdot j]$



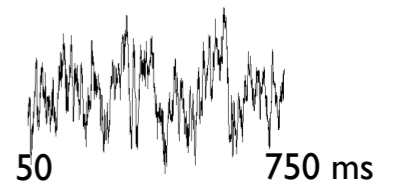
ifft

Synthesis of signals of each trial with parameterized phase distribution

 $x'_i(t)$


N samples signal

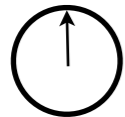
...

 $x'_n(t)$


N samples signal

C)

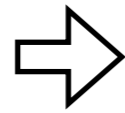
Generation of circular gaussian random distribution of numbers

 $X[f]$


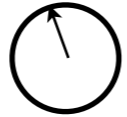
Computing mean phase $[\phi_{(f)}]$ and stdv

 $X[f]$

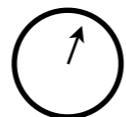

n' scalars (n trials)



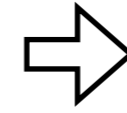
Replacement of each phase value in the original complex coefficients

 $X_i[f]$


...

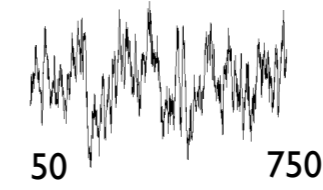
 $X_n[f]$


$[A_{(n,f)} \cdot \cos(\phi_{(n',f)}) + A_{(n,f)} \cdot \sin(\phi_{(n',f)}) \cdot j]$



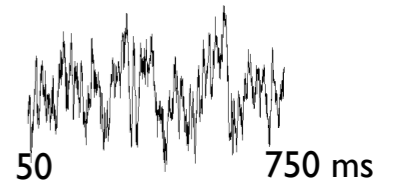
ifft

Synthesis of signals of each trial with parameterized phase distribution

 $x'_i(t)$


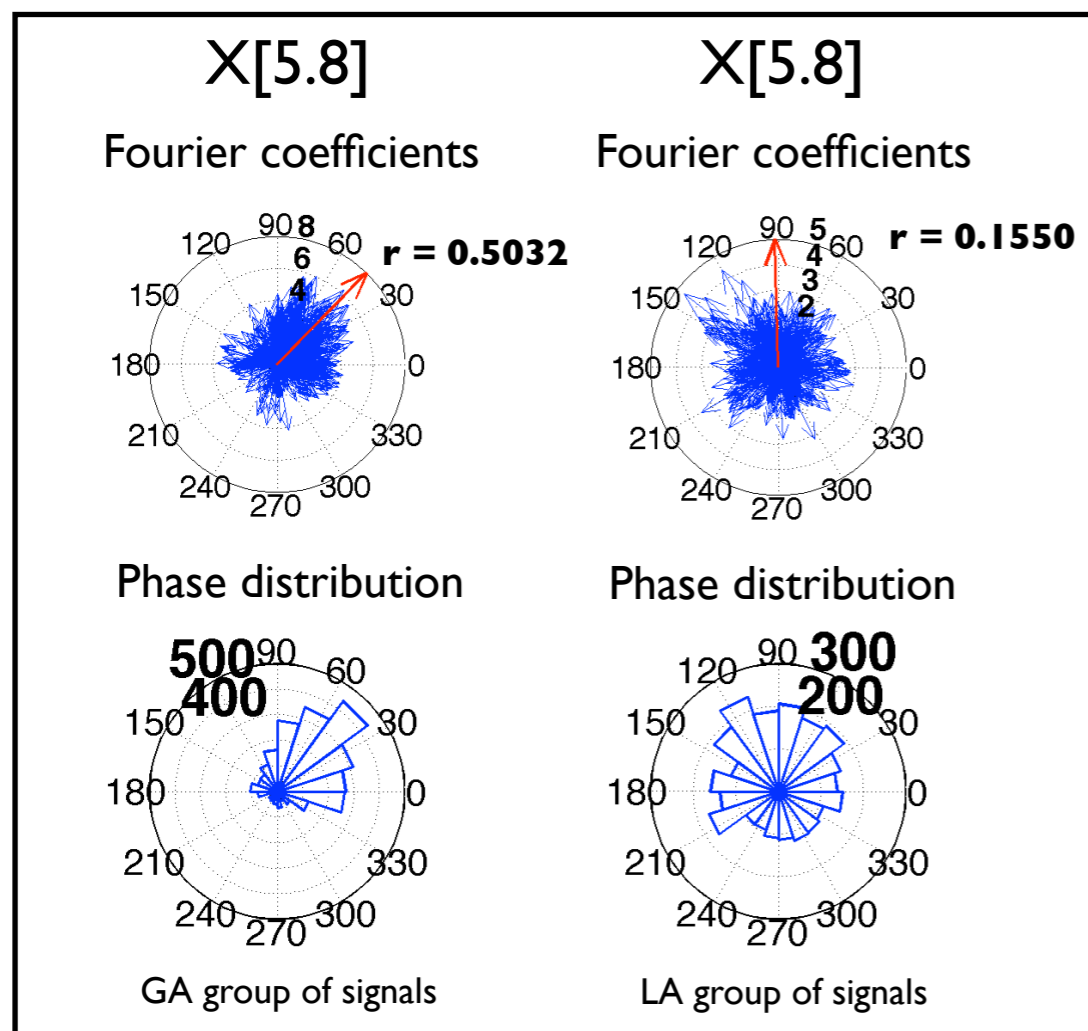
N samples signal

...

 $x'_n(t)$


N samples signal

D)



E)

