Procesamiento de Señales e Imagenes

Ingeniería Biomédica

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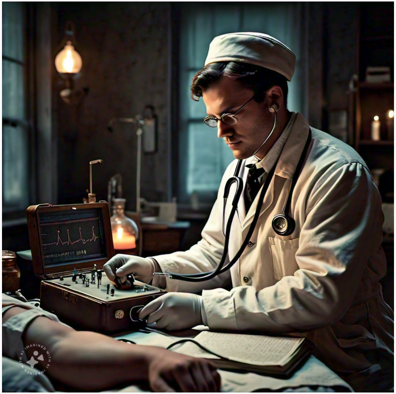
Procesado de Señales e Imágenes Médicas - PSIM

Introduction

Biosignals

- Bio - That came from a biological being
- Signal - A signal is a function that conveys information about a physical phenomenon.
- Biosignals - The search for information from living systems to know its health state



Introduction

Biosignals

The codification of biosignals into variations: * Electrical * Mechanical * Chemical * Thermal

Introduction

Energy	Variables (Specific Fluctuation)	Common Measurements
Chemical	Chemical activity and/or concentration	Blood ion, O_2, CO_2, pH, hormonal concentrations, and other chemistry
Mechanical	Position Force, torque, or pressure	Muscle movement, cardiovascular pressures, muscle contractility, valve, and other cardiac sounds
Electrical	Voltage (potential energy of charge carriers) Current (charge carrier flow)	EEG, ECG, EMG, EOG, ERG, EGG, and GSR
Thermal	Temperature	Body temperature and thermography

Figura 1: Taken from Semmlow et al

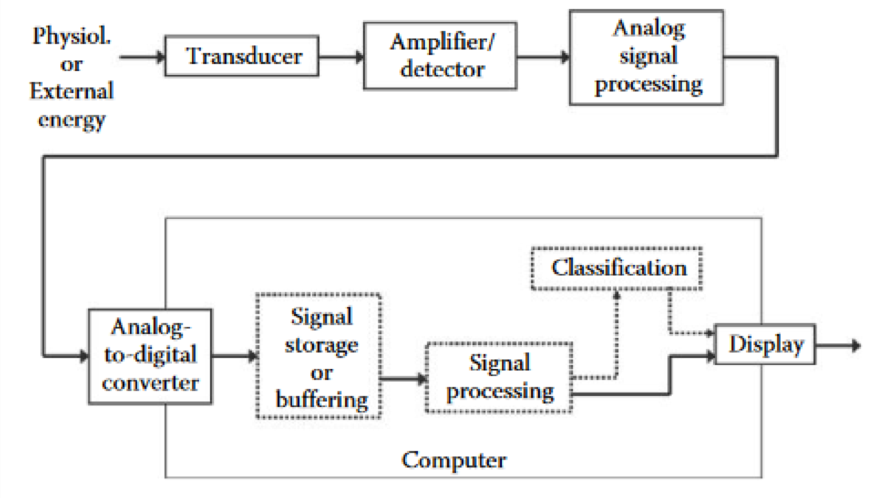


Figura 2: Taken from Semmlow et al

Time line

Biomedical Signals:

- 1791: Luigi Galvani discovers electrical signals in living tissues (frog legs)
- 1830s: Carlo Matteucci studies electrical signals in the heart
- 1887: Willem Einthoven invents the first electrocardiograph (ECG)
- 1900s: James Mackenzie develops the first clinical ECG machine

Time line

Biomedical Signals:

- 1920s: Electroencephalography (EEG) is developed by Hans Berger
- 1930s: Electromyography (EMG) is developed by John Humphrey and others
- 1940s: Development of the first commercial ECG machines
- 1950s: Signal processing techniques are applied to biomedical signals

Time line

Biomedical Signals:

- 1960s: Digital signal processing and computer analysis of biomedical signals emerge
- 1970s: Biomedical signal processing becomes a recognized field
- 1980s: Development of Holter monitoring (24-hour ECG)
- 1990s: Advances in signal processing and machine learning applied to biomedical signals

Time line

Biomedical Signals:

- 2000s: Development of wearable devices and mobile health (mHealth) technologies
- 2010s: Emergence of big data analytics and cloud computing in biomedical signal processing
- 2020s: Integration of artificial intelligence (AI) and machine learning (ML) in biomedical signal processing

Time line

Biomedical Images:

- 1895: Wilhelm Roentgen discovers X-rays, leading to medical imaging
- 1900s: X-ray technology improves with development of modern X-ray tubes
- 1913: Albert Salomon develops mammography
- 1920s: Ultrasound technology is developed by Karl Dussik and others

Time line

Biomedical Images:

- 1930s: Nuclear medicine emerges with development of radioactive tracers
- 1950s: Computed Tomography (CT) scans are developed by Godfrey Hounsfield and Allan McLeod Cormack
- 1960s: Development of medical ultrasound imaging
- 1970s: Magnetic Resonance Imaging (MRI) is developed by Richard Ernst and others

Time line

Biomedical Images:

- 1980s: Digital image processing and analysis techniques are applied to biomedical images
- 1990s: Advances in MRI and CT scan technology, including 3D imaging
- 2000s: Development of functional MRI (fMRI), diffusion tensor imaging (DTI), and other advanced MRI techniques
- 2010s: Emergence of artificial intelligence (AI) and machine learning in medical imaging

Time line

Additional Milestones:

- 1950s: Development of medical electronics and instrumentation
- 1960s: First medical imaging computers are developed
- 1970s: Development of digital image processing and analysis software
- 1980s: Emergence of medical imaging informatics and PACS (Picture Archiving and Communication Systems)
- 1990s: Development of telemedicine and teleradiology
- 2000s: Emergence of electronic health records (EHRs) and health information exchanges (HIEs)
- 2010s: Development of personalized medicine and precision health initiatives

Part I: Probability and Statistics (Repaso)

Events, Sample Space, Experiments

Definition

An **experiment** is a physical procedure that produces some kind of result.

Definition

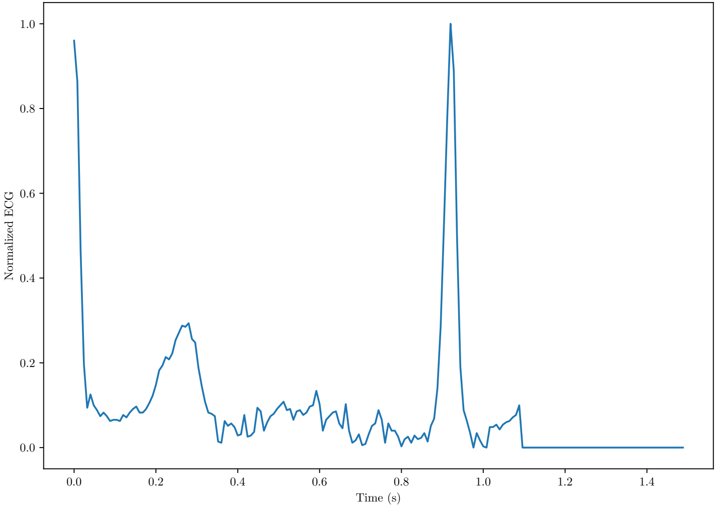
An **event** is a set of experiment's possible results.

Consejo

A **sample space** is the set of ALL possibles results of an experiment.

Events, Sample Space, Experiments

Graph



Code

```
data = np.genfromtxt("../../data/mitbih_train.csv", delimiter=
ecg1 = data[1, :-1]
time = np.array(range(0,len(ecg1)))/125
fig = plt.figure()
plt.plot(time, ecg1)
plt.xlabel("Time (s)")
plt.ylabel("Normalized ECG")
```

Sample Space

```
print("Maximun Value: "+ str(ecg1.max()))
```

```
Maximun Value: 1.0
```

```
print("Minimun Value: "+ str(ecg1.min()))
```

```
Minimun Value: 0.0
```

Result

```
print(ecg1[np.random.choice(ecg1.shape[0], 1, replace=False)])
```

```
[1.]
```

Dataset

Name: ECG Heartbeat Categorization Dataset.

URL:
https://www.kaggle.com/datasets/shayanfazeli/heartbeat?resource=downloa

Probability Axioms

For the given events A and B that are in a sample space S:

Axioms

- $0 \leq P_r(A) \leq 1$
- $P_r(S) = 1$
- If $A \cap B = \emptyset$ then $P_r(A \cup B) = P_r(A) + P_r(B)$
- If $A \cap B \neq \emptyset$ then $P_r(A \cup B) = P_r(A) + P_r(B) - P_r(A \cap B)$
- $P_r\left(\bar{A}\right) = 1 - P_r(A)$
- If $A \subset B$ then $P_r(A) \leq P_r(B)$
- $P_r(A|B) = \frac{P_r(A \cap B)}{P_r(B)}$

Random Variable

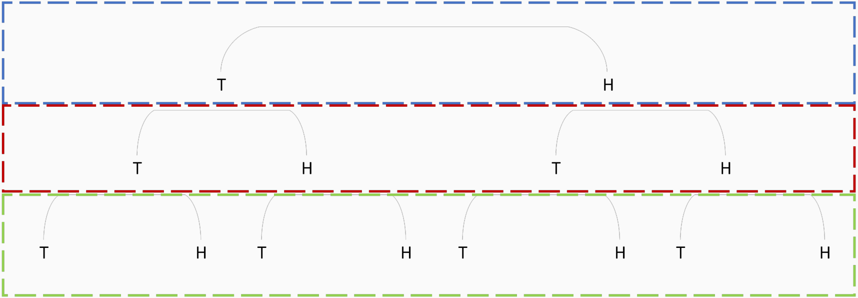
Definition

A random variable is a real valued function of the elements of a sample space, S . Given an experiment, E , with sample space, S, the random variable maps each possible outcome of E.

Definition

The probability mass function (PMF), $P_X(x)$, of a random variable, X, is a function that assigns a probability to each possible value of the random variable, X.

Random Variable



Random Variables

Conditions

Discrete

$$\sum_{\chi \in X} P_X(\chi) = 1$$

Continuous

$$\int_{-\infty}^{\infty} P_X(\chi)\, d\chi = 1$$

Expected Values

Discrete

$$\mu = \sum_{\chi \in X} \chi P_X(\chi)$$

Continuous

$$\mu = \int_{-\infty}^{\infty} \chi P_X(\chi)\, d\chi$$

Variance

Discrete

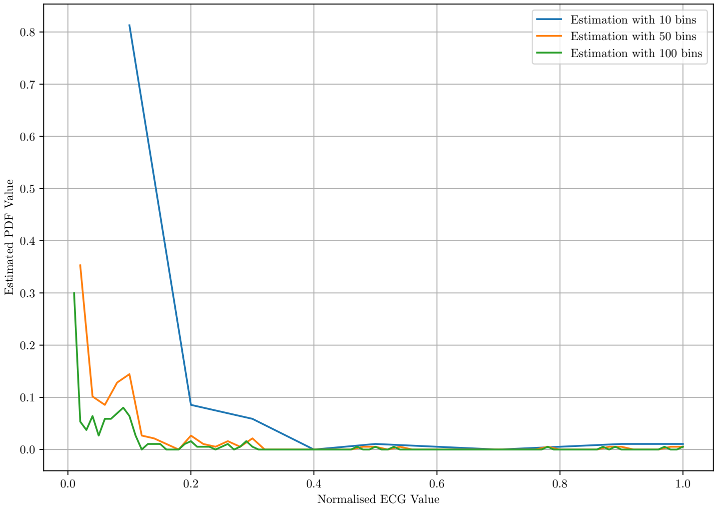
$$\sigma^2 = \sum_{\chi \in X} (\chi - \mu)^2 P_X(\chi)$$

Continuous

$$\sigma^2 = \int_{-\infty}^{\infty} (\chi - \mu)^2 P_X(\chi)\, d\chi$$

PDF Estimation

Graph


Estimation with 10 bins
Estimation with 50 bins
Estimation with 100 bins
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Estimated PDF Value
0.0
0.2
0.4
0.6
0.8
1.0
Normalised ECG Value

Code

```
counts01, bin_edges01 = np.histogram(ecg1, bins=10, density=Tr
counts02, bin_edges02 = np.histogram(ecg1, bins=50, density=Tr
counts03, bin_edges03 = np.histogram(ecg1, bins=100, density=T
fig01=plt.figure()
plt.plot(bin_edges01[1:], counts01/sum(counts01), label="Estim
plt.plot(bin_edges02[1:], counts02/sum(counts02), label="Estim
plt.plot(bin_edges03[1:], counts03/sum(counts03), label="Estim
plt.legend()
plt.grid()
plt.xlabel("Normalised ECG Value")
plt.ylabel("Estimated PDF Value")
```

Exp. Value

```
0.09001020772910533
```

Variance

```
0.02551116143316462
```