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Part I

Fundamentals

1 Introduction

The advancement of electronic devices went through the silent yet pivotal revolutions such as solid-state technology and integrated circuit miniaturization, among many others. However, through merging with the information and communication technologies (ICT), the increasing electronic integration was able to open new perspectives and markets in modern society. The ability to compute and to communicate is among the basic needs of the human community, and the progress of the ICT technologies showed unforeseen scenarios where in some cases – surprisingly – machines greatly surpassed our natural skills. However, in the enduring efforts to make artificial systems behave like humans, few areas are still lagging behind, and one of those is the ability to sense the environment as we do. In this framework, the pervasive implementation of sensing devices in consumer electronics is a highly pursued electronics industry paradigm. The number and variety of sensors implemented in consumer and industrial devices increased dramatically in the past decades: handled devices, automotive, robotics, healthcare, and living assistance.

Unfortunately, artificial sensing requires an approach beyond the borders of information science with the necessity to cope with an incredible number of physical and chemical transduction processes. The interaction with the environment of synthetic systems still shows open issues both at the transduction and at the information processing levels.

Designing sensing devices is always an exciting and challenging task. Very often, the ultimate question is: “Will we be able to detect it?” The answer is hidden in both the technology capabilities and the environment status, and it is not clear, at first sight, where the limitation of the approach is and the reason for the failure. Therefore, the arguments should not be treated as a collection of individual cases but with a general approach using the appropriate tools of abstraction and formalization, with a constant look to the biomimetic inspiration of sensing. In doing so, adopting a strategic and theoretical perspective, we can foresee the integration of massive computation with the sensing capabilities as one of the next incoming revolutions of information engineering.

This first chapter aims to set up the framework on which the book will be shaped, and it is intentionally based on informal descriptions of concepts. This is a nonrigorous approach but is a fundamental step toward an abstraction process about artificial sensing: the ideas behind the general definition of sensors, their main performance-limiting processes, and essential tradeoffs. Using this inductive approach, we will first define concepts, leaving the formalization to the following chapters of the book. If the reader is facing this field for the first time, the arguments could appear vague and fuzzy; thus, this chapter should be eventually reread as the *last* one.

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1.1 Sensing as a Cognitive Process

The concept of a sensor would not exist without life. To grow, reproduce, and survive, any organic entity should perceive external signals to evaluate them, either as an opportunity or a danger. *Sensing* is not a mathematical or physical abstraction derived by inorganic matter, but it is a biological process since any living being should perceive, measure, and evaluate external stimuli to take *actions*. As with many other engineering concepts, this *feedback* model is taken from nature, and sensing is the primary input of such a loop mechanism.

Focusing on human beings, the word *sensor* is derived from the verb *to sense*, referring to the capabilities of human beings to perceive reality by means of sight, hearing, taste, smell, and touch. Sensing is a fundamental part of what is referred to as cognitive sciences, an interdisciplinary field aimed at studying the human mind and knowledge processes.

It has been common practice to analyze the sensing process in interdependent stages such as *sensation*, *perception*, and *consciousness*. The definitions and the borders between these domains significantly differ among the scientific (in a broader sense) communities. However, there is a general agreement on this sensorial experience segmentation. This partition is also reflected in artificial sensing systems.

Sensation is the primary process of receiving, converting, and transmitting information resulting from the stimulation of sensory receptors. Sensory stimuli are taken from the environment by means of physical transduction processes such as those operated by the eyes, where the photons coming from the scene are focused onto the retina in the same manner as a photo camera. The cones and rods of the retina work as transductors, detecting external energy from every single photon and sending the information by means of electrical messages to the brain. On the other hand, perception is the process of selecting, identifying, organizing, and interpreting sensory information. It is not a passive reception of stimuli but early processing: the information is collected, organized, and transmitted by nerves to the brain. Edge detection of objects in seeing and touch is an example of perception. Finally, consciousness is the more elaborated knowledge process: it is the brain's deepest interpretation of neural responses to sensory stimuli. It involves the capacity to sense or perceive and active use of those abilities, depending on previous experience. Humans can experience conscious and unconscious perception. If we relate it to machines, definition, context setting, learning, and adaptation could be possible processes ascribing to a sort of artificial "consciousness." Here, the concept of consciousness is restricted to a functional/phenomenal process, distinguished from the problem of self-awareness where implications are highly speculated in philosophy, with open issues.

In the past centuries, when there were weak boundaries between scientific and philosophical studies, the sensing process was highly conjectured, especially when it was considered a fundamental step for human perception and knowledge. The connection of sensory stimuli with the brain was observed and studied since the time of the

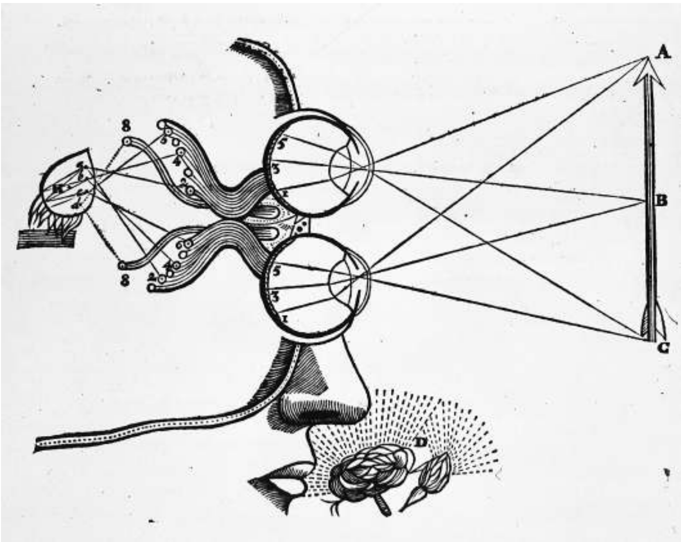

Figure 1.1 Picture taken from R. Descartes, *Tractatus de homine et de formatione foetus*, 1677 (edited posthumously), showing the process of seeing and smelling.

ancient Greeks and in Leonardo da Vinci's monumental work. Among others, it is interesting to note how Descartes remarkably analyzed in greater detail the sensing process in some of his writings, which were very useful in contributing to a general framework of cognitive sciences. As shown in Fig. 1.1, sensorial stimuli (sight and smell) are conveyed into an inner part of the brain, where they are interpreted. Even if some physiological aspects were not correct and Descartes's speculations were far beyond the pure phenomenological aspects of the matter (still unresolved and on debate today), the organization of the sensing process in several steps was profoundly analyzed, introducing modern concepts.

Helmholtz, maybe one of the last polymaths, gave another example of deep analysis of the sensing process in the nineteenth century. In his works (see excerpt illustrated in Fig. 1.2), he gave seminal contributions in the field of visual and auditory perceptions, envisioning a profound relationship between sensing and cognitive sciences. He claimed that human perception should be studied by the *process's physical, physiological, and psychological character*s. He even attempted to justify the perception of beauty related to the sensing process in some of his works.

It is no coincidence that the Greek word *aisthanesthai*, meaning "to perceive by senses and by the mind, to feel" is at the root of the word *aesthetics*: a branch of philosophy dealing with the perception and appreciation of art, taste, and beauty.

To summarize:

- Sensing is a biomimetic concept. Sensors engineering has frequently borrowed functionality models from life sciences psychophysiology and cognitive studies.
- A sensor should not be considered a pure transducer but part of an artificial cognitive process to grab as much information as possible from the environment.

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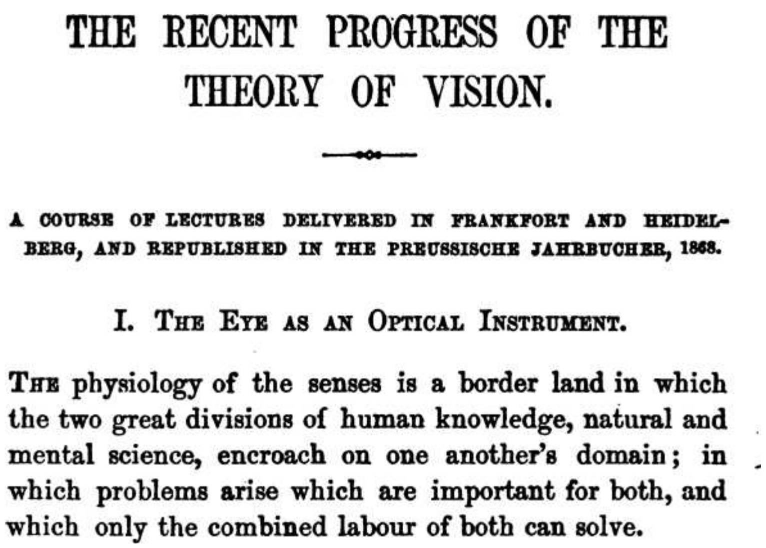

THE RECENT PROGRESS OF THE THEORY OF VISION.

A COURSE OF LECTURES DELIVERED IN FRANKFORT AND HEIDELBERG, AND REPUBLISHED IN THE PREUSSISCHE JAHRBUCHER, 1868.

I. THE EYE AS AN OPTICAL INSTRUMENT.

THE physiology of the senses is a border land in which the two great divisions of human knowledge, natural and mental science, encroach on one another's domain; in which problems arise which are important for both, and which only the combined labour of both can solve.

Figure 1.2 Excerpt from the *Popular Lectures on Scientific Subjects*, by H. von Helmholtz, 1873 (translated from German) envisioning the need for a strong relationship between the sensing and the cognitive processes.

1.2 Aiming at a General Definition of Electronic Sensors

In electronic engineering, the word "sensor" embraces a broad class of systems designed for highly different applications. A "sensor" could be roughly referred to as "a system that transduces physical stimuli into data." However, this definition is too vague and does not take the essence of artificial sensing; thus, a closer look should be taken to understand the standard framework better.

Figure 1.3 shows four examples of systems referred to as "sensors": a weight scale, a microphone, a heart rate monitor, and a machine vision system. They all collect stimuli from the physical environment and convert them into data; however, they are dealing with increasing complexity to achieve the related tasks.

A scale operates a static force measurement. We do not care about the variation of weight within the measurement timeframe. On the other hand, the microphone needs to follow the pressure variation (sound) on a surface versus time, and its time-domain properties are a fundamental aspect of its design. Next, a heartbeat sensor uses patterns in ECG signals associated with heartbeat events. Finally, a machine vision system deals with many images to detect/count defective objects. The idea is that any application identifies specific conditions of the signal to be identified and measured by a custom sensing system. However, the idea of classifying sensors according to the kind of signal could be misleading.

We are looking for not the stimulus itself, but something more complex hidden in primary stimuli and is referred to as *information*. In simple words, the information content is the essence of what we are looking for in the sensing process. The concept of

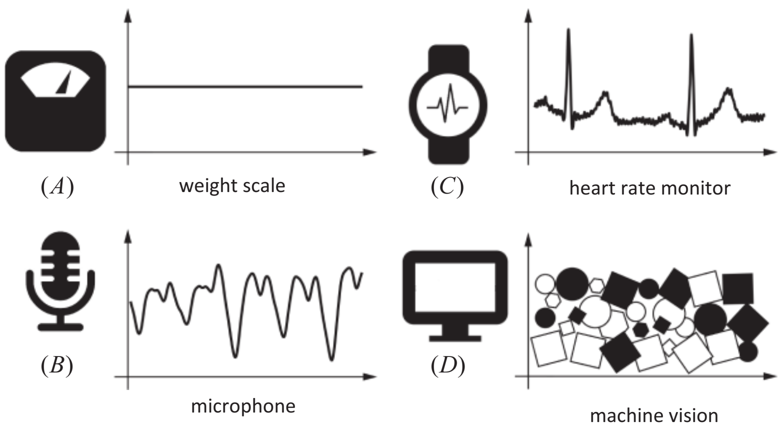

Figure 1.3 Input signals of systems commonly referred to as sensors. (A) Weight scale readout. (B) 1 ms of microphone recording from Etude no. 21 for piano by F. Chopin. (C) 2 s of heart rate biopotential recording. (D) A 2-D machine vision image processor.

information has been extensively treated and formalized in other disciplines; at the moment, it corresponds informally to the amount of knowledge that we gain during the sensing process aiming at the specific task application. We will use a more formal approach to the issue in Chapter 3.

1.2.1 Signals and Information

To illustrate the role of the information in the sensing process, we will use examples. In Fig. 1.4A is shown a heartbeat detector. The sensor's main task is to detect the number of beats in a given period of an ECG signal using a decision threshold. We informally link this to the "information" necessary for our application to understand the concept. The three signal examples of Fig. 1.4A are taken from a set of all possible ECG waveforms in the same time period, and we refer this to as *samples* in the *signal space*. In the first two cases, the system counts 8 beats, while in the last one, only 7. Therefore, we associate the result in a measurable space, referred to as *information space*. In other words, we say that samples in the signal space could be mapped in points in the information space. The acquisition process of a sensor is a correspondence between these two spaces. We will always refer to discrete information space.

In the second example of Fig. 1.4B, the sensing system should detect the number of circles/squares in images. Even in this case, the four sampled images belong to a very large signal space, for example, composed of all possible images of N × M black-and-white pixels. However, the "information" is relatively smaller than the signal space and could be organized in a two-dimensional space where the variables are the number of circles and the number of squares, respectively.

In these two examples, it is easy for human perception to identify the information in the signal space at first sight and check if the sensor system has correctly detected our task. However, there are other cases in which the information is more hidden than

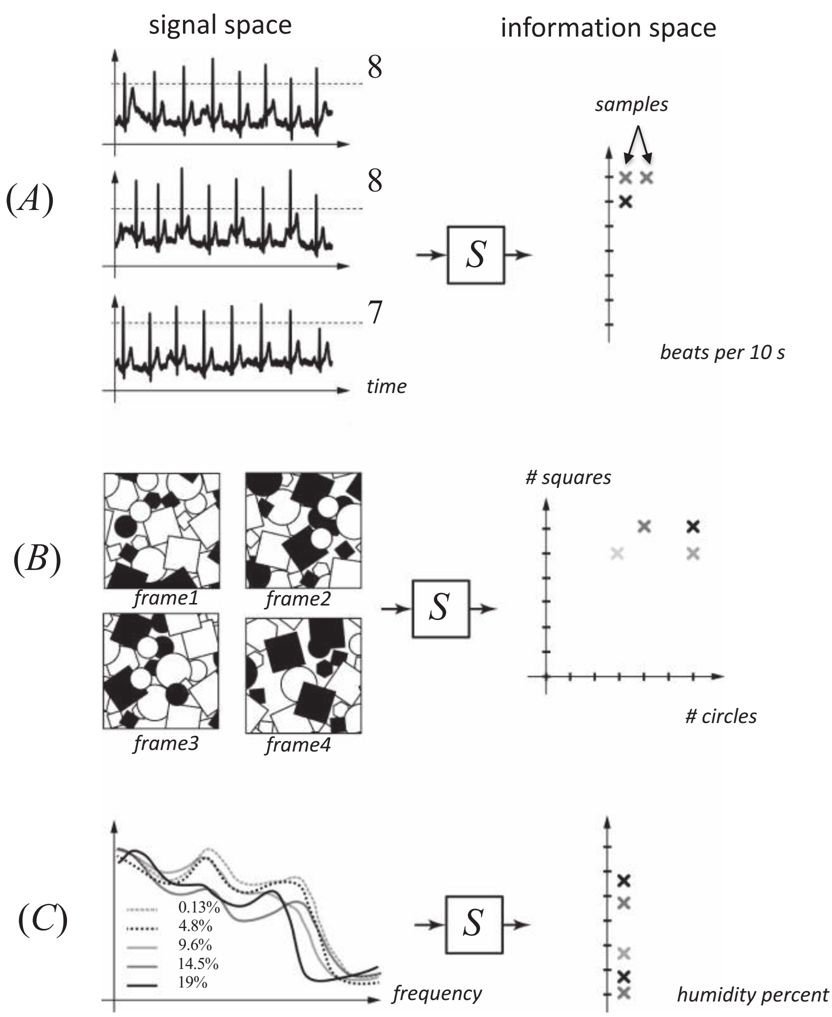

Figure 1.4 Signal and information spaces. (A) Biopotential heartbeat detector using a threshold. (B) Machine vision object counter. (C) Impedance spectrum humidity detector. Note that the first two examples have a discrete information space while the last is a continuous space.

previous examples, and machines could outperform human perception. For example, in the case of Fig. 1.4C, the signal is composed of five measured microwave impedance spectra related to a material having different water content (humidity). The idea is to use these spectra to implement a microwave humidity sensor, where the information is the percent humidity. It is hard to see any regular or monotonic behavior in spectra or in parts of them with respect to the stimulus (humidity). Our intuition concludes that there is no clear relationship between the humidity of the material and the spectra. In other words, it is not easy to see any significant information in the signal itself. However, suppose the signal is treated by suitable mathematical processing. In that case, we can set up a linear predictive model to detect the humidity based on microwave spectra so that signals can be mapped into distinguishable and ordered levels in the information space. The latter example shows that the information could be very hidden in signals, even beyond human capabilities to distinguish them in raw data. For this reason, in these cases, the information to be extracted is often referred to as *latent variables*.

The preceding examples are related to cases of different *complexity* of the task and require different processing resources to extract the information.

To summarize:

- The sensing process should be defined by a *task*, which qualifies the kind of *information* that should be measured. Thus, the application (task) determines the characteristics of the information space.
- *Signals* are functions representing states of the sensed environment carrying information. All the possible configurations of signals define the signal space.
- The information space has smaller dimensions of the signal space, and it is discrete. This means that the multiple elements of the signal space may have the same element in the information space.
- The sensing process is a function implying that each *sample* of the signal space has a correspondence in the information space.

1.2.2 The Simplest Case of an Analog-to-Digital Interface

The previous section identified a distinction between signals and their information content, mapped into the information space. However, if we refer to the simple analog-to-digital (A/D) conversion of a signal in the "analog domain," we can match more easily the two spaces since the analog value itself encodes the information. We can better understand this with the cases illustrated in Fig. 1.5. In Fig. 1.5A is shown a time-varying biopotential signal that is monitored by an A/D interface. Our task is to know the biopotential value evolution with respect to time, and thus it is precisely the information that we need. The A/D converter associates a specific analog value of the signal full scale with a binary-encoded discrete value. Therefore, the discrete values of the A/D converter are easily represented in the information space. The correspondence is made by associating an analog value with the converter's closest discrete value. The case of Fig. 1.5B is even more straightforward: the information is the static analog value of a weight sensor. Therefore, each measure (sample) is directly mapped in the information space. As before, multiple analog values may be mapped into the same coded value by the converter.

In summary:

- In the simple case of an A/D interface, the association between *information* and *signal* is closer because the signal value itself *represents* the information that we need to detect.
- The correspondence is made by associating an analog value with the closest discrete level of the A/D converter.

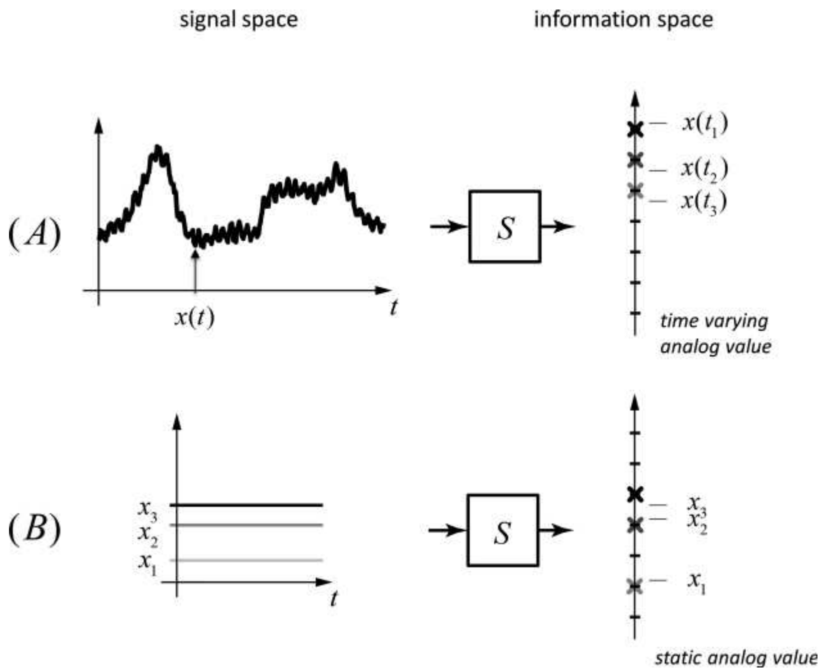

Figure 1.5 Sensing process in time-varying (A) and static (B) analog signals. The analog value of the signal space is associated with the closest discrete value of the information space.

1.2.3 The Role of Errors

Unfortunately, the sensing process's physical implementation is necessarily affected by *errors* due to the stochastic nature of random processes and nonidealities. Errors arise from either the environment or the sensing system itself and its nonperfect detection capabilities. Let us look at Fig. 1.6, where a biopotential is used to detect heartbeats utilizing a threshold as in Fig. 1.4A. In the absence of noise, during the time-lapse, we measure 8 beats, as shown in Fig. 1.6A. Now, assume that the sensing process is noisy and the same waveform as in Fig. 1.6A with added noise is shown in Fig. 1.6B. If we use the same detection approach, the count is no longer 8 but rather 10. The random process of noise changes the threshold crossing cases: there are some points (e.g., point M) that were not crossing the threshold before (without noise), while now they do, thanks to noise contribution. Conversely, there are other points (e.g., point N) that were crossing the threshold in the previous case, and now they do not pass the level because of the perturbation of noise. If we repeat the same procedure on a signal containing 8 beats in the presence of the noise, we may at one time count 7, another time 9, another time again 8, and so on. This means that we cannot say that the count is certain but, in the presence of noise, we can say that the "estimation of the count is given by 8 ± 2." Therefore, the presence of noise determines an *uncertainty* (Chapter 2) of the measure of ± 2 counts. The uncertainty due to noise could be visualized in the gray area across the tick equal to 8 in Fig. 1.6.

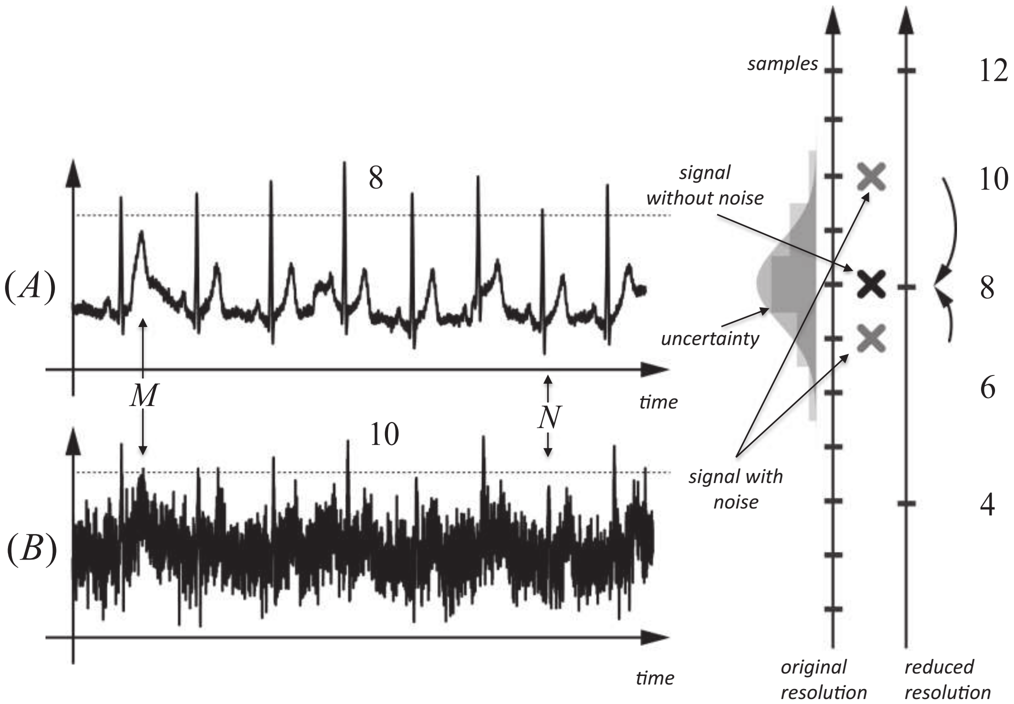

Figure 1.6 Effect of resolution reduction due to noise. Biopotential recording to calculate heartbeat (A). Same biopotential signal but with noise added (B). The addition of noise determines the increase of uncertainty of detection and thus a decrease of resolution.

In this example, the presence of errors (or noise) changes the information space situation. If we could have counted single beats without noise before, now we have an uncertainty of ±2 counts. Therefore, previous levels are no longer truly distinguishable from each other because the *same* signal could give counts in the interval 8±2 due to noise. This fact reveals that the information space subdivision is not appropriate because the sentence "count = 8" has information similar to that one of "count = 10." This results in a *misclassification* because we classify 8 counts, although, in reality, they might be 10 or vice versa. This means that we have a high probability that the affirmations mentioned above reflect the same signal condition due to errors. This could be seen pictorially showing that the same uncertainty area covers samples. Therefore, it could be better to reduce the number of subdivisions (e.g., by grouping 4 levels) so that "count is between 6 and 10" and "count is between 2 and 6" has more significance from the information point of view because there is a lower probability that the two sentences correspond to the same signal. In this case, any sample giving a value in the uncertainty zone, identified by 8 ± 2, will be associated with the center of the interval, whose value is 8. In other words, by enlarging the classification zones by considering uncertainty, we reduce possible misclassification errors.

We can thus refer to the subdivisions of information space as *resolution levels*. In the presence of noise, we might set the resolution level of the order of the uncertainty so