

# Hidden Context Influence on Pattern Recognition

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**Abstract**—The influence of hidden additional information concerning the circumstances of input data acquisition on the quality of decisions based on the data is considered. An analogue to the intuition influencing natural decision making is indicated. The problem of contextual information in decision making based on Bayes rule, on reference data sets in various applications as well as of scene analysis by numerous examples is illustrated.

**Keywords**—*decision making, hidden information, intuition, pattern recognition, scene analysis.*

## 1. Introduction

Since the very beginning of the pattern recognition development as a scientific discipline (i.e., since the middle of 1950's) many attempts were made to make the artificial pattern recognition methods as effective as the natural one were made. Till now, the early expectations of a possible quick reaching this goal by using the approaches to pattern recognition based on artificial neural networks, geometrical, statistical, formal linguistic, algebraic or any other advanced types of models and based on them algorithms only partially came to be true. In many application areas (e.g., in medical diagnosis, biology, criminology, geophysics, etc.) a verification of the computer-aided pattern recognition results by those of human pattern recognition takes place rather than the reverse. Such a situation exists not only because of a much lower number of artificial neural networks' elements than this of the neurons in a natural human brain or because of too low computer performance rates, but also because of an imperfection of the actually available artificial recognition models and methods. One of the human mind's properties which in the to-date artificial intelligence methods is neglected is the **intuition**. The diagnoses made by the experienced medical specialists, even if based on apparently similar or the same input diagnostic data, are usually more accurate than those made by the low-experienced physicians as well as those made by the computer-aided diagnostic systems. This fact is usually explained by the intuition supporting the experienced specialist's thinking and by a lack of the intuition in the two other cases.

Many attempts to explain the phenomenon of intuition were made by the philosophers (e.g., by Aristotle, Plato, R. Descartes, I. Kant, J. Locke, H. Bergson, etc.) [1].

They assumed a primacy of intuitive cognitive process over the one based on the observations. On the other hand, L. Wittgenstein assumed that such metaphysical concepts as intuition in scientific researches should not be taken into considerations [2]. This point of view on the intuition was shared by some naturalists in the past century (e.g., by J. B. Watson and other authors representing a behavioural approach in psychology [3]). Nevertheless, many examples of subconscious processes existence in human thinking and of their influence on human behaviour can be shown [4]. S. Freud tried to explain many aspects of human behavior by subconscious mental processes [5]. The role of the intuition in creative thinking and in discoveries was analyzed by many authors, like R. S. Siegler and E. Stern [6], A. Motycka [7], M. Polanyi [8] and, in particular, in mathematics by B. L. J. Brouwer [9], J. Hadamard [10]. A simple definition of intuition as "...a direct, by a preliminary analysis and/or reasoning not preceded knowledge about something..." is given in [11]. Similarly, D. G. Myers [4] defines intuition as our "ability to getting access to immediate knowledge, prompt inspection into it without observations or reasoning". A. P. Wierzbicki [12] formulates the most general, intuition concerning question: "...what is intuition: is it a supernatural ability of human mind distinguishing it from animals and producing infallible truths or is it rather a very powerful but natural ability, common with animals, producing new ideas but such that require justification and evaluation?"

The paper presented below is an extended version of a non-published plenary speech delivered at the 7th International Conference on Computer Recognition Systems CORES held in Wrocław, Poland, in May of 2011. The following problem is here considered: is intuition a natural mental property worthy and possible to be simulated by artificial decision making systems? If so, then neglecting any its metaphysical aspects, what could it mean from an information processing point of view? In the context of the main problem the following particular items are considered below: a working definition of intuition based on informational approach is proposed in Section 2. Influence of additional information on the decisions based on Bayes rule are described in Section 3. Similar problem concerning pattern recognition based on reference sets is considered in Section 4. The role of contextual information in scene analysis is shortly illustrated in Section 5. Conclusions are formulated in Section 6.

## 2. Intuition – a Working Concept

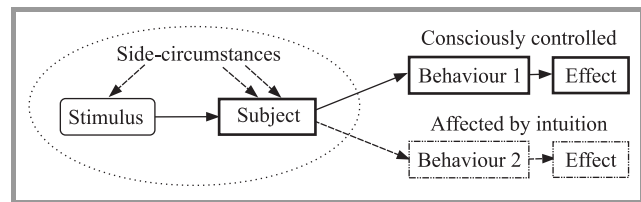
Before answering the first of the above formulated questions two remarks should be made:

1) The hidden intuitive mechanisms governing creative (e.g., mathematical, artistic, musical, etc.) thinking are different from those influencing animal or human behavior in suddenly arising situations. In the first case, a sort of unconscious evoking and associating of possible solutions of a problem, while in the second case rather evoking some remembered in the past similar situations and their effects take place. In addition, the results in both cases are different. In the first case, it is an “illumination”, i.e., a sudden thought about a possible problem solution, while in the second case it may be an impression of an irrational fear, disapproval, distrust, etc., or in an opposite case it may take the form of a hope, belief, confidence, etc. The last type of intuition has been created, probably by a natural evolution, as a form of adaptation of living beings to a necessity of effectively react to unexpected events of high living importance: a danger of an attack, an occurrence of a potential sexual partner, a possibility of food reaching, etc.

2) Not all intuitively suggested decisions are correct or useful. D. G. Myers [4] describes numerous examples of wrong decisions inspired by intuition. In particular, he remarks that mathematically optimal decisions differ essentially from intuitive decisions based on the most impressive, similar to the present one cases. A noise heard in darkness not always is caused by a wild animal; a smile not always means that somebody is well predisposed to us. Our first impression after arrival to an unknown town is not always correct. The examples show that our intuitive reaction to sudden event is not always justified in a given situation, sometimes it may be evidently unfavourable or wrong.

The simulation of intuition in artificial decision making systems, if possible, is thus desirable only if it helps in system's action improving or in its better decisions making. For this (and in particular, for pattern recognition) purpose an informational model of intuition seems to be suitable. Intuition can thus be defined as an ability of a subject to unintended admission, in certain attending side-circumstances, affecting his (its) behavior or decisions by remembered impact of analogous circumstances on experienced in the past situations.

The informational model of intuition is schematically presented in Fig. 1. It shows that the behavior of a subject and following from it effects evoked by the same stimulus may be different, because of neglecting or unconscious taking into account additional information about the circumstances attending the stimuli. This corresponds to the well known situations of some human decisions that are assessed as “irrational” by other people, because they subconsciously have been affected by information that is unavailable to other people, kept in the mind of the decision making subject.



**Fig. 1.** Informational model of subject's behaviour affected by intuition.

Side-circumstances in Fig. 1 mean in this context that information about them has not been directly included into the decision rules. Otherwise speaking, they constitute a sort of informational context of decisions made under incompleteness of information. Intuition reduces the information incompleteness level by taking into account additional information about the circumstances which may modify the decision. Therefore, an additional (hidden) information may affect the recognition and increase its quality. In the nature, past information influence on human behavior is connected with sub cortical informational processes in the mind. In computer systems such influence may consist in automatic (i.e., hidden for the user) registration of data concerning circumstances attending current decision-making, and in using them in future pattern recognition acts. The concept of including programs that automatically start operations into the computer system is not new; each operational system contains many hidden operations protecting the user against errors, and application programs contain operations protecting against data misusing. The question is whether the above-mentioned cases example an “intuition” of the computer systems. It seems not as they are limited only to an automatic formal analysis of input data or to a hidden control of the calculating operations.

As a more advanced case, it can be mentioned the M. Minsky's concept of “daemons”, special procedures included into the knowledge representing systems based on “frames”. The role of “daemons” consists in automatic completing the contents of frames by lacking elements, explicitly to the system not provided but existing in the input data in a hidden form [13]. However, even in this case additional information does not concern the circumstances attending the past decisions of the system. Close to the “artificial intuition” concept is this of information retrieval systems equipped by the mechanisms of the replies modification by taking into account the currently modified informational profiles of the users [14]. From the user's point of view, the system able to guess the probable user's requirements for information is equipped with a sort of “intuition”. However, this “intuition” is limited to user's preferences only. Below, a more general case of “intuition” consisting in affecting the current pattern recognition by the information about the circumstances of past pattern recognition acts will be considered. Taking into account that additional information affecting current decisions are based on collected in the past experiences, the “artificial intuition”-based information systems can be considered as a sort of self-learning systems. However, like in natural

intuition, this additional information may be charged with a dose of uncertainty.

### 3. Bayes-Rule-Based Pattern Recognition

The Bayes-rule based pattern recognition methods belong to the most early elaborated ones [15]. The simplest case of two recognized classes of objects (patterns),  $C_1$  and  $C_2$  will be here reminded. Let  $U$  denote a multidimensional vector space whose elements (vectors)  $\mathbf{u}$  represent the objects of a given physical nature. It is assumed that the object occurs randomly. Hence, the classes  $C_1, C_2$  can be described, respectively, by the conditional probability densities  $v(\mathbf{u}|C_1), v(\mathbf{u}|C_2)$  and by their a priori probabilities  $p_1, p_2$  where  $p_1 + p_2 \equiv 1$ . We define a decision function as a function assigning to any vector  $\mathbf{u} \in U$  of, as one of the two above-mentioned classes:

$$\chi : U \rightarrow \{C_1, C_2\}. \quad (1)$$

Let us also denote by  $P_{1|2}$  a conditional probability of recognition of an object  $\mathbf{u}$  as belonging to  $C_1$  when, in fact, it belongs to  $C_2$ , and by  $P_{2|1}$  a conditional probability of recognition  $\mathbf{u}$  as belonging to  $C_2$  when, in fact, it belongs to  $C_1$ . The optimal Bayes sense decision function  $\chi(\mathbf{u})$  is the one that minimizes the mean decision risk:

$$R = P_{1|2} + P_{2|1}. \quad (2)$$

It is known [15] that such function should have the form:

$$\chi(\mathbf{u}) = \begin{cases} C_1 & \text{if } \lambda(\mathbf{u}) > \Lambda, \\ C_2 & \text{if } \lambda(\mathbf{u}) < \Lambda, \end{cases} \quad (3)$$

(if  $\lambda(\mathbf{u}) = \Lambda$  any of two decisions is admissible), where  $\lambda(\mathbf{u})$  is a pre-decision function:

$$\lambda(\mathbf{u}) = \frac{v(\mathbf{u}|C_1)}{v(\mathbf{u}|C_2)} \quad (4)$$

and

$$\Lambda_0 = \frac{P_2}{P_1} \quad (5)$$

is a threshold level [15]. In the simplest case, if  $P_1 = P_2 = P$  it is  $\Lambda = 1$  and the rule (3) takes a simpler form:

$$\chi(u) = \begin{cases} C_1 & \text{if } v(\mathbf{u}|C_1) > v(\mathbf{u}|C_2), \\ C_2 & \text{if } v(\mathbf{u}|C_1) < v(\mathbf{u}|C_2), \end{cases} \quad (6)$$

as it (in a one-dimensional case) is illustrated in Fig. 2.

For  $\Lambda_0 = 1$  a threshold point  $u_0$  between the  $C_1$  and  $C_2$  decision areas, according to Eq. (6) is given by the equation  $v(\mathbf{u}|C_1) = v(\mathbf{u}|C_2)$ . In such case, the decision risk  $R$  is equal to the sum of the areas under the curve  $v(\mathbf{u}|C_1)$  for  $u > u_0$  and under the  $v(\mathbf{u}|C_2)$  for  $u < u_0$ . Till now, no ‘‘intuition’’ affects the decision. However, let us assume that

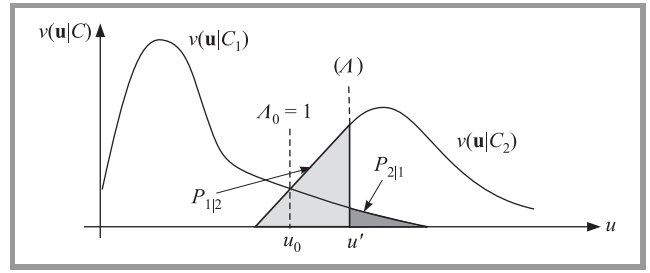


Fig. 2. Bayesian pattern (signal) recognition rule.

for certain reasons, the errors consisting the recognition of  $C_2$  instead of  $C_1$  lead to much larger ‘‘costs’’ than recognition of  $C_1$  instead of  $C_2$ . In such case, a user intuitively may believe that it is better to shift the threshold point from  $u_0$  to  $u'$ ,  $u_0 < u'$ , as shown in Fig. 2. Evidently, the risk  $R$  given by Eq. (2) is in this case increased (as being equal to the sum of the gray areas in Fig. 2). It can be shown that it corresponds now to a new threshold value  $\Lambda$  in the rule (3), for  $P_1 = P_2 = P$  given by:

$$\Lambda = \frac{P_2 r_{1|2}}{P_1 r_{2|1}} = \frac{r_{1|2}}{r_{2|1}}, \quad (7)$$

where  $r_{1|2}/r_{2|1}$  denotes a relative cost assigned to the errors of the ‘‘ $C_1$  instead of  $C_2$ ’’ with respect to this of ‘‘ $C_2$  instead of  $C_1$ ’’ type. This relative cost can be assessed due to remembered effects (e.g., for the user) of wrong decisions made in the past, i.e., of connected with them circumstances.

The above-presented example of intuitive cautiousness influence on pattern recognition can easily be extended on more realistic, parametric Bayesian decision rules. For this purpose, it will be assumed that the conditional probability density functions of input signal have the form  $v(\mathbf{u}|C_1; \gamma_1), v(\mathbf{u}|C_2; \gamma_2)$ , where a binary recognition problem once again is considered and  $\gamma_1, \gamma_2 \in \Gamma$ ,  $\Gamma$  being a set of *passive parameters*, i.e., unknown parameters specifying the form of probability distribution. Despite the fact that passive parameters directly don’t carry any useful information, their knowledge improves the quality of the decision-making rule [16]. The pre-decision function under passive parameter takes the form:

$$\lambda(\mathbf{u}) = \frac{v(\mathbf{u}|C_1; \gamma_1)}{v(\mathbf{u}|C_2; \gamma_2)}, \quad (8)$$

where the values  $\gamma_1, \gamma_2 \in \Gamma$  in a classical Bayes decision rule are exactly known, but in a more general case it may be only approximately given. However, let us assume that a decision maker is, due to his experience, convinced that a perceptible increment (decrement)  $\Delta\beta$  of external parameters (circumstances) may cause the corresponding changes of the passive parameters  $\gamma_1, \gamma_2$ . He doesn’t know any exact functional dependence between the increments  $\Delta\beta$  and those of the passive parameters. However, for any given  $\Delta\beta$  one expects that  $\Delta\gamma$  may be *positive* or *negative*, its value may be *small (S)*, *moderate (M)* or *large (L)* or it may

be negligible ( $N$ ). One interprets the last notions as some fuzzy variables characterized by their membership functions in the L. Zadeh sense [17], as illustrated in Fig. 3. This justifies a correction of the pre-decision function according to the formula:

$$\lambda'(\mathbf{u}) = \frac{v(\mathbf{u}|C_1; \gamma_1 + \Delta\gamma_1)}{v(\mathbf{u}|C_2; \gamma_2 + \Delta\gamma_2)}, \quad (9)$$

the values  $\Delta\gamma_1, \Delta\gamma_2$  being chosen as those maximizing the membership functions  $\mu(\Delta\gamma)$  of the fuzzy variables ( $S, L, M$  or  $N$ ).

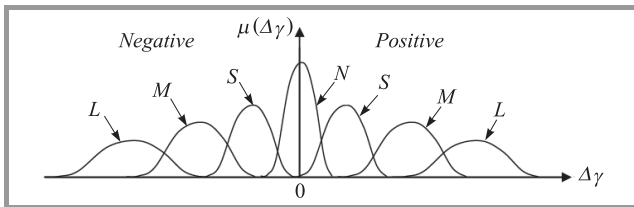


Fig. 3. Membership functions of fuzzy sets describing assumed relative external parameter's influence on passive parameter increments:  $N$  – negligible,  $S$  – small,  $M$  – moderate,  $L$  – large.

An intuitive correction of probability distribution parameters describing similarity classes can be illustrated by the following example.

Let's assume that in order to detect the most dangerous points on the roads in a town several points of road traffic monitoring have been selected. The vehicles' velocity was measured and the corresponding histograms have been calculated. Two classes of points:  $C_0$  – non-dangerous and  $C_1$  – dangerous have been assumed to exist and to be recognized according to the following rule: a point belongs to  $C_0$  if no more than 50% of passing vehicles exceed the speed limits, otherwise it belongs to  $C_1$ . According to the classification rule, the medians  $m$  of the velocity histograms  $h(V)$  for each monitoring point  $P_i, i = 1, 2, 3, \dots$ , were calculated and the classification rule took the form:

$$P_i \in C_0 \quad \text{if} \quad m_i < V_{0i},$$

$$P_i \in C_1 \quad \text{if} \quad m_i \geq V_{0i},$$

where  $m_i$  is a calculated median and  $V_{0i}$  is a previously established speed limit for the given monitoring point  $i$ . However, several histograms of the same median may be of different form, as illustrated in Fig. 4. The histogram  $A$

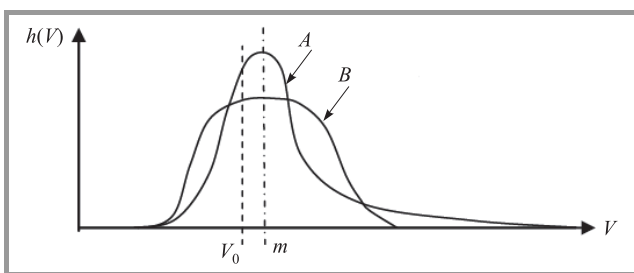


Fig. 4. Approximated histograms of car velocities in the roads; admissible speed limit = 100%.

is characterized by high asymmetry (*skewness*) and low flatness (*kurtosis*), while histogram  $B$  is rather symmetrical and more compact. An experience tells us that the type  $A$  histogram corresponds to the more dangerous situation than  $B$  because it shows that a relatively great rate of vehicles exceeding the speed limits on an extremely high level. As a consequence, a point  $P_i$  satisfying the condition  $m_i < V_{0i}$  and thus classified as  $P_i \in C_0$  in fact, should be reclassified as  $P_i \in C_1$  if it is found that its skewness is high-positive.

### 4. Pattern Recognition Based on Reference Sets

The reference (learning) sets are widely used in pattern recognition in methods based on the assumption that a functional description of patterns (*similarity classes*) is not possible a priori. Reference sets can thus be defined as sets of correctly classified objects representing the similarity classes. It is assumed that the reference sets  $S_1, S_2, \dots, S_N$ , where  $N$  is the number of recognized patterns, are mutually disjoint finite subsets of the observation space  $U$  unambiguously assigned to the similarity classes. Recognition of an object  $\mathbf{u}$  consists in indication of the closest element to  $\mathbf{u}$  in a certain set reference set  $S_n, n \in [1, 2, \dots, N]$ . However, the reference sets can be collected in various ways. It is illustrated by Fig. 5 where composition of reference sets  $S_r, S_c$  is shown, representing, respectively, two classes of objects denoted symbolically by "rhombs" ( $\blacklozenge$ ) and "circles" ( $\bullet$ ).

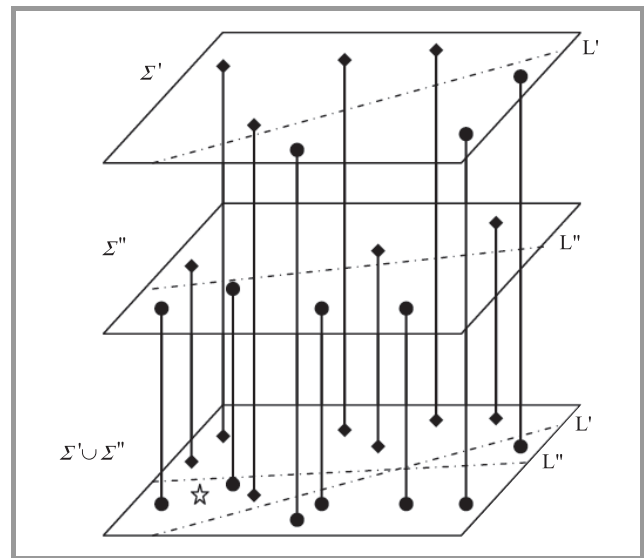


Fig. 5. Collection of reference sets as sums of subsets provided from two independent sources.

In this example it is assumed that the reference sets have been obtained by summing the corresponding subsets:  $S'_r \cup S''_r$  and  $S'_c \cup S''_c$  collected independently in two different external circumstances attending the observations shown on the planes  $\Sigma'$  and  $\Sigma''$ . Straight lines  $L'$  and  $L''$  separate the



subsets  $S'_r$  and  $S'_c$  collected on  $\Sigma'$  as well as  $S''_r$  and  $S''_c$  collected on  $\Sigma''$ . No straight line separates exactly the joined subsets  $S'_r \cup S''_r$  from  $S'_c \cup S''_c$  (both,  $L'$  and  $L''$  admit two misclassifications).

Let's assume that the next object, denoted by a "star"  $\star$  has been observed and should be classified. Evidently, it will be classified as a "rhomb" if  $L'$  and as a "circle" if  $L''$ , as a separating line is used. However, let us assume that it is known that external circumstances of the "star" observation were closer to those attending the  $\Sigma'$  than the  $\Sigma''$  circumstances. In such case it is reasonable to use the  $L'$  separating line and to recognize the "star" as a "rhomb".

The above-presented situation can also be differently interpreted. Different credibility levels can be assigned to the observations collected on  $\Sigma'$  and  $\Sigma''$ . For instance, we believe more that the data on  $\Sigma'$  are correct than those on  $\Sigma''$ . The next "star" object can be recognized by using the "k most similar objects" (k-MSO) approach. In such a case a similarity measure  $\sigma(\omega_i, \omega_j)$  is defined among the pairs of objects in the observation space satisfying the standard conditions [18]:

$$\left. \begin{array}{l} \text{I. } \sigma(\omega_i, \omega_i) \equiv 1, \\ \text{II. } \sigma(\omega_i, \omega_j) \equiv \sigma(\omega_j, \omega_i), \\ \text{III. } \sigma(\omega_i, \omega_j)\sigma(\omega_j, \omega_k) \leq \sigma(\omega_i, \omega_k). \end{array} \right\} \quad (10)$$

According to the k-MSO recognition rule, an observation  $\omega_i$  is recognized as belonging to a similarity class  $C_n$  if among k most similar to  $\omega_i$  objects in the reference set  $\Sigma' \cup \Sigma''$  most belong to  $S'_n \cup S''_n$ . However, if the elements of  $\Sigma''$  are less credible than those of  $\Sigma'$ , the similarity measures between  $\omega_i$  and the elements of  $\Sigma'$  should be taken into account with a weight reducing their influence on the recognition result. This can be done by replacing the value  $\sigma(\omega_i, \omega_j)$  by  $\sigma^\beta(\omega_i, \omega_j)$  where  $\beta > 1$  is a reducing the similarity measure parameter.

The idea of taking a "hidden" inner structure of the reference sets into account has a particular importance in computer-aided medical diagnosis.

As an example, the case of a reference set of total cholesterol rates construction is presented. Data have been extracted from the records gathered in several dozens of ana-

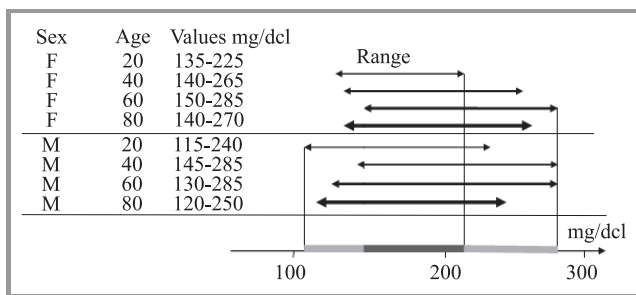


Fig. 6. Construction of a rough set of total cholesterol rate in patients of different sex (F – female, M – male) and age. The rough set indicated in the bottom-scale: black thick – surely belonging values, grey thick – possibly belonging values, black thin – surely not belonging values (data unpublished, provided by prof. Jerzy Janecki).

lytical laboratories in Poland. The measured cholesterol levels primarily have been grouped according to the geographical regions, sexuality and age of patients. Part of the analysis results are shown in Fig. 6. The range of the recorded cholesterol rates depends on both the sexuality and the age of the patients. An averaged group of cases can be obtained as an algebraic sum of the sets corresponding to the particular cases. An interval  $D^* = [150 \div 225]$  mg/dcl is a common part of all particular intervals while  $D_* = [115 \div 285]$  mg/dcl is the minimal one covering all recorded cases. Both intervals describe a rough set (in the Z. Pawlak sense [19]) of total cholesterol levels occurring in all categories of human patients. However, for medical diagnosis a set of "normal" cholesterol levels is desirable. For this purpose, one can select from  $D^*$  a "core" consisting of its middle 3rd part, i.e. a sub-interval  $\underline{D} = [175 \div 200]$  mg/dcl. Then a pair of intervals

$$S = \{\underline{D}, D^*\} = \{[175 \div 200], [150 \div 225]\}$$

describes a rough reference set of cholesterol rates corresponding to the patients "in norm". A computer system may decide that a patient is:

- "certainly in norm" if his cholesterol rate belongs to  $\underline{D}$ ,
- "possibly in norm" if it belongs to the difference  $D^* - \underline{D}$ ,
- "certainly out of norm" if it does not belong to  $D^*$ .

However, the cases recognized as "probably in norm" can be verified if the age and sexuality is taken into account and specific rough reference sets are available instead of the averaged one. For example, let us assume that the patient is 80-year-old woman primarily as "probably in norm" diagnosed. In this case a specified rough reference set is given by a pair of intervals:

$$S_{F,80} = \{[183 \div 227], [140 \div 270]\}.$$

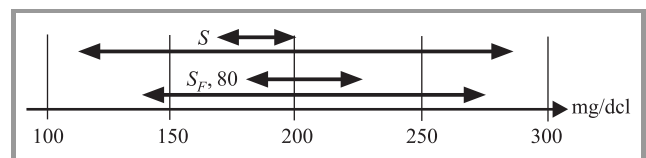


Fig. 7. Comparison of an averaged S and a specific SF, 80 rough reference sets.

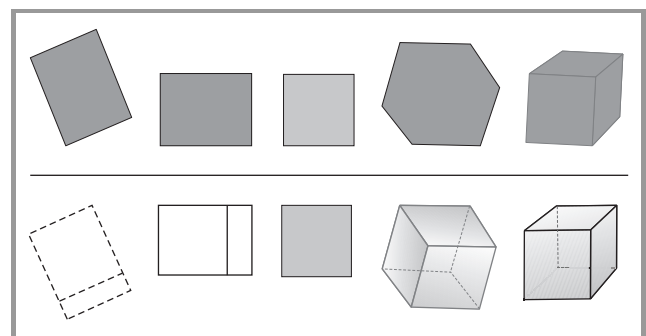


Fig. 8. Recognition of a "square" or a "cube projection" depending on the context.



**Fig. 9.** Examples of scenes: (a) city view, (b) a garden view whose computer interpretation may lead to incorrect results.

In Fig. 7 the averaged and specific rough reference sets are compared. In the case of using the averaged reference set to medical diagnosis the “certainly in norm” interval is relatively small. Any based on it medical diagnosis can be corrected if the decision maker is able to use the specific reference sets instead of the averaged one, and additional information about the patient’s age and sexuality is taken into consideration. It can be observed that in such a case a correction may consist of replacing:

- some “certainly in norm” recognitions by “possibly in norm”,
- some “possibly in norm” recognitions by “certainly in norm” or by “certainly out of norm”.

The influence of contextual information on decision-making can also be illustrated by an example of geometrical figures recognition. In the upper row of figures shown in Fig. 8, a *square* among the rectangles and the hexagons can easily be recognized. However, in the lower-row context the same figure rather as a *projection of a cube* among other cube projections will be recognized.

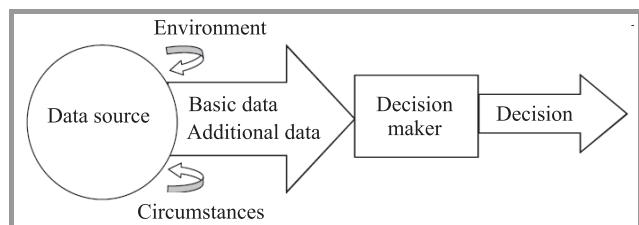
It follows from the above-given examples that additional information about the reference sets may substantially influence the results of pattern recognition.

## 5. Scene Analysis

Scene analysis is a domain of pattern recognition where contextual information plays a particularly important role. A *scene* can be defined as a collection of distinguishable objects in a physical 3D space satisfying some geometrical and/or topological relations. A correct image contents understanding and description needs without additional contextual knowledge (experience, intuition, etc.) is practically impossible.

This can be illustrated by the examples presented in Fig. 9. The image 9a can be recognized and described by an “intelligent” computer system as “A church tower and a house of equal heights in a city environment”, while the image 9b as “An old man’s face wearing glasses and two small human (dwarf?) figures on both its sides”. Only additional information about 3D city perspective in the case of 9a and possible design of a garden in the case of 9b makes the correct interpretation of the images.

Hence, besides the basic input data, a correct decision making system should thus, besides the basic input data, take into account some additional data concerning a widely defined environment of the data source and of data acquisition circumstances, as shown in Fig. 10. The problem is how to control the process of additional data acquisition, storage and selection for a given decision process. In natural



**Fig. 10.** Recognition of a “square” or a “cube projection” depending on the context.

thinking this is mostly a subconscious process. In artificial decision-making systems it may be hidden to the user. However, it should be a property programmed by the system designers.

## 6. Conclusions

The role of intuition in human behavior has been known since ages and a lot of concepts explaining the nature of intuition has been proposed in the literature. From an informational point of view intuition can be considered as a sort of additional information influencing decision making besides the basic data taken into account by a decision-maker. The numerous examples show that such additional information may be substantial in the decision making quality. In some cases a correct decision making without taking into account additional information concerning the observed objects environment or data acquisition circumstances seems impossible. On the other hand, inclusion into the decision process additional information stored by the system can be considered as a substitution of intuition in computer-aided decision system, analogous to the natural intuition influencing the human decision making. The investigation of the problem seems thus to be an open and important research problem in computer applications.

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