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NOTES ON A LINGUISTIC DESCRIPTION AS THE BASIS FOR AUTOMATIC IMAGE UNDERSTANDING

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The main paradigm of image understanding and a concept for its practical machine realisation are presented. The crucial elements of the presented approach are the formalisation of human knowledge about the class of images that are to be automatically interpreted, a linguistic description and the realization of cognitive resonance.

Keywords: automatic understanding, computer vision, digital images, semantics, image processing.

1. Introduction

Computers can collect images, store them in databases, present them on webpages, send through the Internet, and perform many kinds of image processing operations. As a result of such operations, the form of an image can substantially change. Moreover, images in computer systems can be analyzed and recognised automatically. Therefore, a new area of computer applications has been developed, namely, computer vision. A scanner or a digital camera cannot substitute for the eyes, so the computer's "vision" needs to be understood in a broad meaning. For a long time it was believed that there was a magic formula for computer vision and its discovery seemed a matter of time. Over time, the approach has changed and it is now believed that in order to have a clear machine vision, one has to combine various elements. The transition from the mechanistic approach to the one based on a "judgment call" or an "expert opinion" is supported by the notion of image understanding. It is now almost indispensable, because while dealing with images, it is not sufficient to focus exclusively on the form. In order to recover the meaning, one needs to analyse the content. Figure 1 illustrates how complex the analysis and recognition of an image can be if one does not take into account its semantic content. If we want to solve a simple task, i.e., to count the number of chairs in an image, it turns out that a single method that describes the image in terms of contours, components, etc. is not sufficient.

The extraction of image meaning from computationally accessible features continues to be a challenge. In image data mining, we aim at retrieving the *meaning* of images, in other words, we aim at *automatic image understanding*.

In computer science, the term *automatic understanding* has appeared in numerous papers, but has not been applied to images. Most papers describing automatic understanding concern the area of applications that deals with text analysis. The solutions they present, often based on semantic networks (Sieckenius de Suza, 2005; Antoniou and van Harmelen, 2008) are very interesting, but they are beyond the scope of this paper. The term *automatic understanding* has acquired a specific meaning, which is used, for example, in machine translation of natural languages, but this area of applications is also out of scope of this paper, dedicated to automatic understanding of *images*. Nevertheless, we start with presenting some information about the text understanding system, which will be useful for explaining the proper meaning of automatic understanding of *images*.

Fig. 1. Example of an image which needs the understanding of its content. Reprinted by permission from (Christensen, 2003).

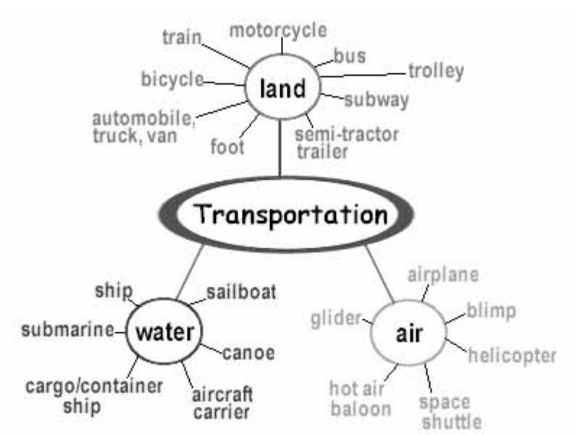


Fig. 2. Example of a simple ontology used for automatic text understanding (source: `http://www.kidbibs.com/images/semantic.gif`).

The highly elaborate automatic understanding tools are used for various purposes, such as automatic retrieval of a text that is difficult to retrieve by means of key words only, automatic document summary, knowledge representation, etc. These tools are founded on ontologies, i.e., content-dependent relations between concepts. Figure 2 shows an example of a simple ontology. Numerous very good papers can be found on text content analysis including very subtle or specific domain related semantic dependencies, and this area of computer science increases and develops now very fast.

At the same time, the topic of automatic understanding of images has been addressed by relatively few authors. Homenda (2006) concentrates on a particular kind of image, namely, music notation. Leś and Tadeusiewicz (2000) advocate the analytic-geometric approach to shape understanding. The work proposes a structural (linguistic) description as the key to a successful image interpretation. Interesting results can be found in (Bowyer *et al.*, 2008), which focuses exclusively on one kind of image,

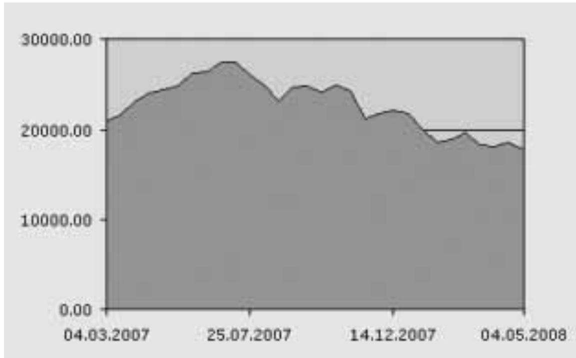


Fig. 3. Image that can be easily interpreted by an expert.

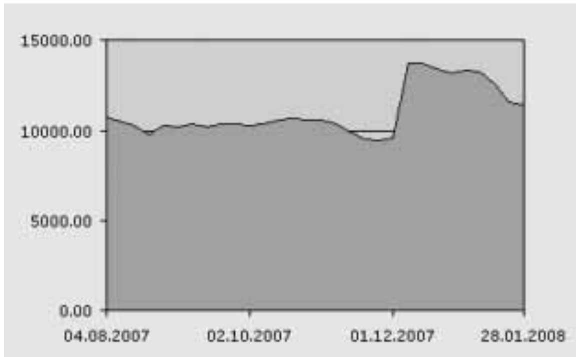


Fig. 4. Image that can help to understand a certain situation.

namely, the image of iris (for the purpose of biometric identification). Automatic understanding of people's images (mainly with the aim to identify them) is discussed in (Hilton *et al.*, 2006). However, the approach presented in that work differs substantially from the one proposed in the paper. The idea suggested here (based on the interaction between visual data and the knowledge previously fed into the system) is related to the one found in (Drummond and Caelli, 2000; Zheng and Tsuji, 1998).

2. Understanding of artificial images

Understanding (even *automatic*) of a text is relatively easy, because every text evokes an expectation of a meaningful content. Thus, it is not unusual to consider a text in terms of *meaning*. Image understanding is a completely different matter. Each image has a specific *form*: size, colour, texture, shape, etc. It can be described in these terms and automatically recognised. However, at first glance, it may seem not to have any content, which to a large extent depends on the form of the image, the presence or absence of some objects, mutual relations between objects, etc. Given the above, can we speak of *image understanding*? Before we answer this question, let us discuss a few examples.

Let us consider Fig. 3 first. It shows a chart, seemingly difficult to disambiguate without additional information. However, after a careful examination of the description of the axes, one can notice that the horizontal axis depicts time, whereas the vertical axis represents money (for example, euros). If we link these observations to expert knowledge about stock market trends at the turn of 2007 and 2008, we understand that the chart line shows share prices (possibly an *economic slump*).

Figure 4 shows a similar chart, which can be used for a more detailed understanding of a certain situation. The chart, analogously to the previous one, can be considered as a reflection of fluctuations in stock market prices. However, the phenomenon shown here is much more interesting than the one observed in the previous case. It is visible that, after a long-term stability, the prices started to rise slightly (around 6 December). This may have increased the investor's confidence and motivated him to buy securities, which resulted in a sudden rise in the line chart. Unfortunately, instead of rising, the prices started to fall and one may have lost all the money invested. Again, the meaning of the chart could be: *investment mistake*.

The meaning was recovered because of the interaction of two factors: the visual information from the image (chart) and the background knowledge about stock market processes. Only when the two sources of knowledge are combined can the image content be understood. The fact that the image (supported by prior knowledge) was sufficient to recover the meaning of the image indicates that an image can have a particular content, which one can try to *understand*. If a human can do it, a computer might be capable of doing it as well. The history of artificial intelligence (computational intelligence) shows that whenever a form of a human intellectual activity has been properly defined and described on the ground of psychology and cognitive science, it is possible to design an intelligent computer program that can imitate cognitive skills of a human being.

The analysis of images in Figs. 3 and 4 illustrates that images do have specific contents, which can be recovered thanks to proper analysis. However, critics may argue that the examples given in Figs. 3 and 4 are artificial, reflecting relatively uncomplicated events and, consequently, their meaning can be easily recovered. The next section deals with images taken from real life, which carry meanings that cannot be easily inferred from a mere form, but must be *understood*.

3. Understanding of real images

With images that represent real situations, recovering the meaning is more difficult, but not impossible. Again, let us use a few examples.

Figure 5 depicts objects that can be identified as people, a building and its elements. Looking at the image, one can say that the people are dressed in a similar way, with one identical element—the cap. Based on prior knowledge, one can infer from the photo that it might have

Fig. 5. Image that requires *understanding*, not only simple analysis.

been taken in China and that the people depicted in it are tourists, who are wearing identical clothes and caps so that they are not lost during a sightseeing trip.

Therefore, dwelling into the meaning (not focusing exclusively on the form) one can *understand* what the image really depicts and what subject matter it represents.

Let us consider the contents of Fig. 6. Similar objects are shown: women, men and cars. However, their meaning is different. Hence, when we search for the same message or the same story, image retrieval on the basis of object analysis can give wrong results.

The aim of this paper is to explain how *computers can be made to understand, ignoring (as much as possible) the form*. The answer is automatic image understanding.

4. Proposed concept of automatic understanding

Notice that, in order to examine the semantic content of a given message, it is necessary to combine the content with prior knowledge possessed by an intelligent agent. This applies to every message (also in the image form) and every object that aims at understanding—even a computer, whose actions result in cognitive analysis defined as automatic understanding. Figure 7 shows a general scheme of understanding. The most important element of the scheme is the cognitive matching process, which joins two streams of information. The first one is connected with an external data source. Taking the data from outside and aiming at the understanding of its merit sense, we must process the data. To be more specific, we must extract from the data the most important features. However, the process of automatic understanding is not limited to this kind of processing. If we aim at understanding data contents, we must refer to the internal resources of knowledge that are located in the mind (natural or artificial) of the agent which tries to understand the data.

Fig. 6. Two images—both showing women, men and vehicles.

The internal resources of knowledge are necessary for the generation of the expectations, which must be satisfied if a merit sense is to be extracted form the data. The internal resources of knowledge act as a hypothesis generator. Each hypothesis suggests a possible way of understanding, which is based on the merit knowledge located in the system. There are various types of knowledge sources. They can be coupled during the learning process, received from human experts, based on experimental analysis of similar examples, etc. However, regardless of its type, a knowledge source can be used for describing the expectations.

The internal resources of knowledge can generate many hypotheses and expectations related to these hypotheses. When the features extracted from the input data match the expectations, a hypothesis becomes more reliable. For a proper data interpretation, we expect more than one match between the stream of data features and the expectations knowledge base. If we obtain many good matches, it means that the automatic understanding process has been successful.

5. Linguistic description as the basis for automatic image understanding

Having briefly discussed the notion of automatic understanding, let us try to outline the basic assumptions of the concept of automatic *image* understanding. Starting with the chart in Fig. 7, we shall try to adapt it to the needs of automatic image understanding. Earlier research in this domain was founded on the scheme proposed by Ogiela *et al.* (2008), whose work was a little more specific for automatic understanding of images (not text messages). The scheme is shown in Fig. 8. There are a few elements that need to be commented on.

First of all, when compared with Fig. 7, the input channel (camera-generated) and internal information link, which carries expectations generated by the knowledge base, are much more elaborate. As shown, the input image should be represented in a special way in the system that is supposed to understand it, and the system's actions cannot be limited to mechanical processing or routine analysis, with possible transition to automatic recognition (not to be mistaken for automatic understanding). The image which is computationally processed (with the aim of content understanding) should be represented in the system by means of linguistic methods, namely, as a chain of gram-

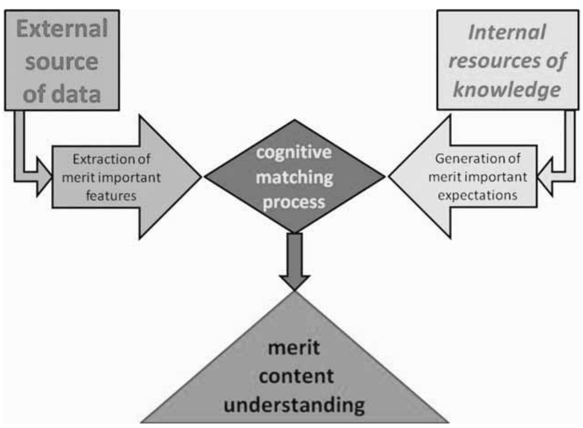


Fig. 7. General scheme of understanding.

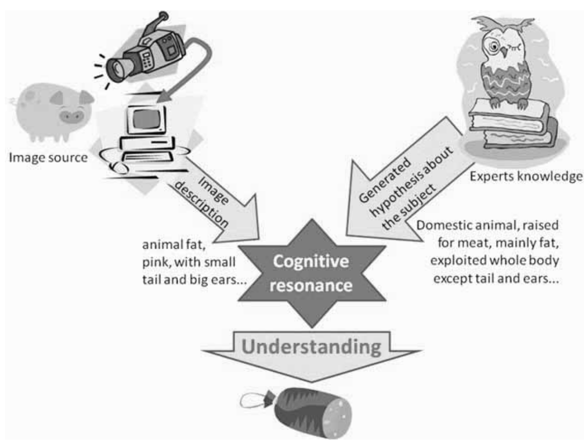


Fig. 8. Method of dealing with images that aims at automatic understanding of their contents.

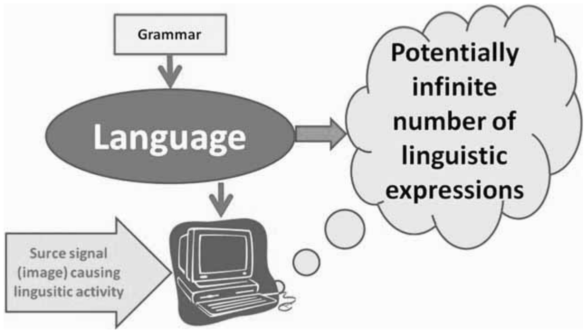


Fig. 9. Language as a tool that enables a device with limited capabilities (computer) to make an unlimited number of records.

mar terminal symbols.

Let us explain why linguistic-based tools are best for automatic image description. The reason is strictly connected with the very nature of the comprehension process, completely different from the process of recognition, which it is frequently mistaken for. When the goal is recognition, we first establish a list of categories by means of which we can classify the objects analysed. Such a classification always comprises a finite number of categories (usually including the category of an "unknown object", indicated in the picture with a question mark). The task of the algorithm that analyses the image is to determine which of the categories a given object belongs to.

Image understanding (achieved by a human, or obtained automatically) means recovering the *implicit* meaning of the image. The difference between recognition and understanding is that the former results in a determined set of elements (solutions provided by the system), whereas the latter is unpredictable and for this reason the set of possible image interpretations contains an infinite number of elements—allowing for the fact that computer is a device of limited capabilities, which might be a serious problem (Fig. 9).

What generates an infinite number of combinations from a finite number of elements is language. For example, the Polish language consists of a finite number of words and a finite number of grammatical rules. However, it allows one to create an infinite number of articles, novels, poems, official documents, etc. This applies also to artificial languages, such as C++, which also consist of a definite number of components and rules. However, they are able to create an indefinite number of programs, with the possibility to constantly create new ones.

6. Role of reasoning

In the literature, the role of reasoning in automatic image understanding has so far been rarely considered because of its difficulty. Let us demonstrate an example. Working with the images given in Fig. 10, we can set the following tasks:

(1) recognition of English and Chinese letters,
(2) recognition of words in English and Chinese,
(3) knowing the meaning of Chinese texts in the images (a) and (c), and reason about the information given in the image (b).

Tasks 1 and 2 can be solved with the use of a classification method. The same method can be applied if there is an explanation in the database (a label) for the combination of letters given in the image (b).

But if no explaining label exists, then the computer can only state an "unknown object". As opposed to a computer, a human who knows English is able to reason about the meaning ("entrance") of information given in the image (b) in Chinese.

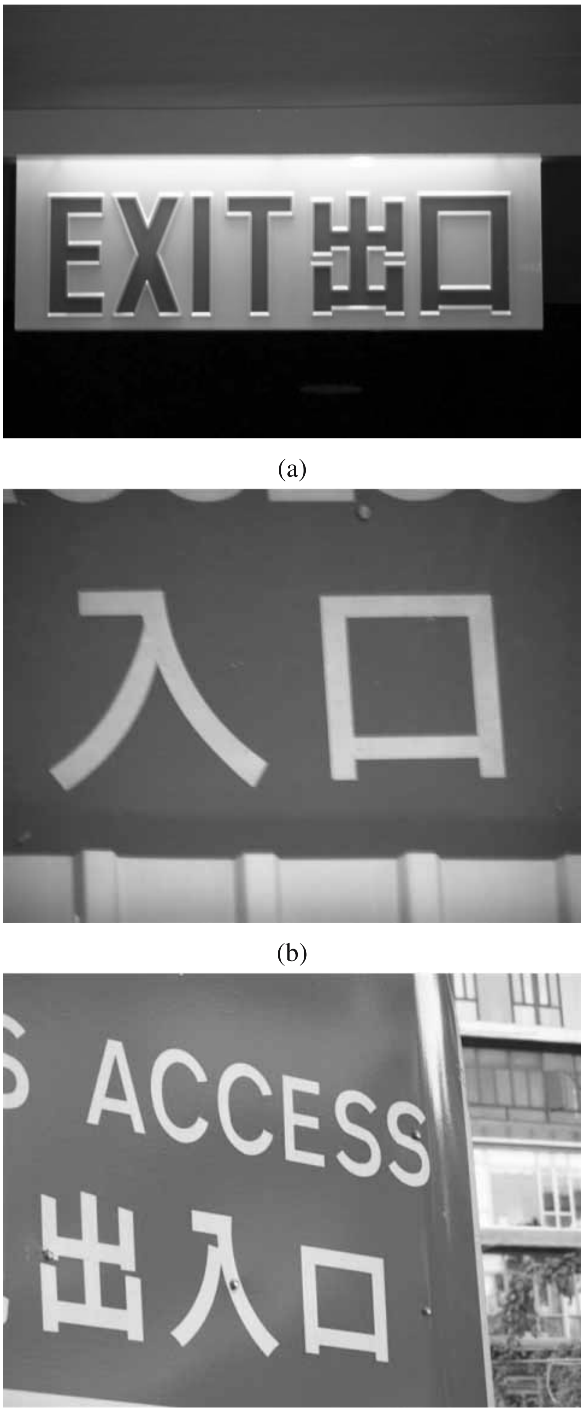
7. Summary

The approach of *automatic understanding of images* described in (Tadeusiewicz and Ogiela, 2004) is devoted to medical applications (Ogiela *et al.*, 2006a; 2006b; 2006c; 2006d; Tadeusiewicz and Ogiela, 2005; Przelaskowski *et al.*, 2007). However, its generality allows us to extract some fundamental issues.

Trying to explain what automatic understanding is and how we can force the computer to understand the image content, we must demonstrate the fundamental difference between a formal description of an image and the content meaning of the image, which can be discovered by an intelligent entity capable of understanding the profound sense of the image in question. The fundamental features of automatic image understanding are as follows:

1. Imitation of the human way in image analysis and in reasoning about the content. An expert and a well-defined field of interest are preferred here. For example, consider medical images of some organ and a restricted class of variations in the image content.
2. Linguistic description of the image content. Examples of languages and grammars used for that purpose can be found in the book (Tadeusiewicz and Ogiela, 2004) and the papers (Tadeusiewicz *et al.*, 2008; Ogiela and Tadeusiewicz, 2001; 2008).
3. The image content linguistic description constructed in this manner constitutes the basis for understanding the image merit content.

The most important difference between all traditional methods of automatic image processing and the new paradigm for image understanding is that there is a feed forward data flow in the traditional methods while in the new paradigm (Tadeusiewicz and Ogiela, 2004) there are two-directional interactions between signals (features) extracted from image analysis and expectations resulting from the knowledge of the image content as given by experts.



(a)

(b)

(c)

Fig. 10. Recognition, classification and understanding by reasoning: (b) EXIT, (c) ??? , (d) ACCESS.

Linguistic-based tools used for the description of images with the view of their automatic interpretation were described in (Ogiela and Tadeusiewicz, 2001; Tadeusiewicz and Ogiela, 2002) and thoroughly discussed in (Ogiela and Tadeusiewicz, 2008). Medical applications are presented in (Ogiela *et al.*, 2006; 2008).

The idea of cognitive resonance appeared in (Ogiela and Tadeusiewicz, 2003) and was discussed in (Tadeusiewicz and Ogiela, 2004), both works being inspiring sources of knowledge for those interested in this topic.

Notwithstanding the research mentioned above, automatic image understanding technology is still in the early phase of development. One of the recent ideas is the application of adaptive potential active hypercontours (Tomczyk, 2005; Tomczyk and Szczepaniak, 2005; 2006) to image content verification (Tomczyk and Szczepaniak, 2007; 2008).

To conclude, the authors sketched here the basis for further research contributing to the development of an efficient methodology of automatic image understanding.

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