Informativeness of visual models

S A Kudzh¹, V Ya Tsvetkov¹² and I B Nomokonov³

¹Russian Technological University (RTU MIREA), Vernadsky Prospekt, 78, Moscow, 119454, Russia
²Research and Design Institute of design information, automation and communication on railway transport, 27, bldg 1, Nizhegorodskaya str., Moscow, Russia
³OGUZ Irkutsk Regional Hospital, Irkutsk, Russia

E-mail: cvj2@mail.ru

Abstract. The purpose of the work is to study the informativeness of visual models. The article reveals the features of the visual perception of images. We described the factors that distort the concept of informativeness as an objective value. The article proves that the perception of visual images cannot be equated with the collection of information using technical devices. We described the content of reception, perception and apperception in visual perception of visual models or spatial images The article introduces a systemic model of informativeness, which shows that the use of pixels as image elements does not evaluate the informativeness, but evaluate the information volume of the image. In order to evaluate the informativeness of visual models, it is recommended to use a visual cluster model. The article introduces a system of key indicators to evaluate the informativeness in the information visual processing.

1. Introduction

Informativeness is an important characteristic of information field objects [1-3]. Visual objects and visual models [4, 5] have the perception and analysis specificity. It makes their informativeness special [6]. The evaluation of informativeness can be considered as the extraction of tacit knowledge [7] from a visual image. The main problem in evaluating the informativeness is the “the dogma of the one-dimensionality” [8]. This dogma is to describe a complex (multidimensional) phenomenon with one indicator. The following inaccuracies are often made when evaluating the informativeness of information objects and models.

A. Informativeness is identified with the amount of information according to C.E. Shannon. Informativeness is often evaluated as the difference in bit entropies for two visual digital images. In this case, the entropy is calculated by the elements, not by the content features of the image.

B. Informativeness is not associated with the loss of information during processing. During visual processing, it is possible to lose the visual image elements which reduce the informativeness.

C. Informativeness is not associated with the presence of noise or third-party elements. Non-informative elements may appear during visual processing and distort the image. For example, as a raster line increases, its thickness and the number of bits on it increase. In these cases, at the intersection of straight lines, new, non-informative elements may appear.

D. Informativeness is evaluated by the number of elements, in particular, by the number of bits when it comes to a raster image. Visual clusters and spatial relations between image elements are not taken into account.
E. Additional factors (relations, connections, background) that exist when evaluating the visual image informativeness or visual informativeness are not taken into account. In practice, when evaluating the visual image informativeness, cognitive analysis is performed, rather than a mechanical collection of information. At the same time, such an important concept of image integrity as gestalt is excluded and not taken into account.

All of this requires a study of visual image informativeness as a special direction.

2. Research methodology
The basis of the research is system analysis, structural analysis, comparative analysis and qualitative analysis. The publications in the field of informativeness, entropy, cognitive modelling, perception of visual information were used as materials.

3. Research results

3.1. Perception of the visual image
The perception of a visual image evokes reception, perception, apperception and cognitive modelling procedures rather than a mere technical collection of the information.

The primary perceiving process at the level of sensory receptors that leads to excitation of the sensors is called reception [9]. In the language of cognitive modelling, reception is associated with the concept of visibility and perceptibility [10]. The result in the information area is a primary information model, for example, as a collection of visual image elements received using sensors.

The secondary perceiving process, which leads to the construction of visual image fragments, is called perception [11], i.e. construction of a nervous model of irritation in the form of a sensory image. In the language of cognitive modelling, perception is associated with the concept of primary interpretability or interpretability of fragments. The result of perception in the information area is a secondary information model, for example, as a collection of fragments of a visual image or a collection of sets of visual images. Perception is sometimes associated with perceiving in which four levels are distinguished: detection, differentiation, identification, assimilation. In fact, detection refers to reception. Differentiation and identification refer to perception. Assimilation refers to apperception. That means that perceiving includes all three processes.

The secondary perceiving process, which leads to the construction of a visual image using fragments, is called apperception [12]. In the language of system analysis, apperception creates a complete image. In the language of cognitive modelling, apperception is associated with the concept of gestalt [13, 14]. The result of apperception in the information area is a unique information model with the pertinence property. Thus, the perception of a visual image cannot be identified with the collection of information using sensors or with the collection of a set of elements. It should be noted that visual perceiving does not collect information but converts the visual image information into an information resource [15].

3.2. System model of informativeness
System analysis makes it possible to display the informativeness model (Inf) as a tuple.

\[ Inf < E, Cl, C, R, Bg > \] (1)

Expression (1) includes the following characteristics: E – elements of an image, Cl – visual clusters in an image, C – connections in image, R – relations (spatial) in image, Bg – background. The background significantly affects the informativeness. For example, when exploring the Arctic territories, a white background formed by snow and ice covers the image that makes pictures non-informative.

An image can include clusters or fragments. There is the concept of visual cluster and visual cluster analysis [16, 17]. A visual image fragment or visual cluster is a complete formation that unites the elements of an image. It is the fragments, not the elements, that create the informativeness of the visual image. For example, a white or black A4 sheet of paper when scanned at a resolution of 300 dpi results in a file of the same size, approximately 28MB. The same can be said about a photographic plate on
which there is no image. But these files and their visual images are not informative. This means that these files lack the following informativeness parameters from the expression (1): Cl, C, R.

If a sheet of the visual image carrier contains a drawing or a meaningful X-ray image, then the parameters Cl, C, R appear. There are always elements (pixels) on a visual raster image. Their number is determined not by the meaningfulness of the image but by the capability of a technical device that converts the background and the image into the same number of elements. Therefore, the number of elements (E expression (1)) and the entropy calculated on their basis do not characterize the informativeness. They characterize only the informational volume. Entropy considers elements and does not consider Cl, C, R, Bg. There is an alternative concept of negative entropy [18] which characterizes not uncertainty as entropy does, but meaningfulness.

Effect of background. Light elements of the image disappear (are absorbed) on a white background. Dark elements of the image disappear (are absorbed) on a black background. Therefore, the background affects the informativeness. It can be reduced if background absorbs elements or fragments of the image. In addition, the background affects the integrity of image perception.

3.3. Key indicators of informativeness evaluation
As an alternative to methods trying to introduce one informativeness indicator, in this work, we propose a set of key indicators or coefficients to evaluate the informativeness. Indicators of informativeness should be complementary [19], i.e. should give an overall agreed evaluation. Indicators of information content should be able to be used as rules for evaluating informativeness in intelligent systems [20].

The coefficients for evaluating informativeness can be introduced if there is an initial image or an original that has the informativeness characteristics

\[ \text{Inf} < E, Cl, C, R, Bg > \]

There is a secondary image or model received as a result of processing or scanning the primary image or formed in the cognitive area of an expert person.

\[ \text{Inf}2 < E, Cl2, C2, R2, Bg2 > \]

The number of elements does not change during scanning and does not depend on the image but on the characteristics of a technical device. Therefore, all other factors affect the informativeness.

We use the following initial data: \( N \) is the number of clusters before processing; \( N_i \) is the number of distorted but interpretable clusters; \( N_l \) is the number of missed or absorbed by the background clusters; \( N_o \) is the number of undistorted clusters after processing; \( N_{ni} \) is the number of distorted and non-interpretable clusters. Thus, the interpretability of image fragments affects visual informativeness.

We introduce the following coefficients characterizing the informativeness. \( K_l \) is the loss coefficient; \( K_{inf} \) is the coefficient of informativeness; \( K_d \) is the distortion coefficient; \( K_{int} \) is the coefficient of interpretability for distorted objects; \( K \) is the coefficient of representativeness. The loss coefficient is defined as the ratio of missing clusters to the total number

\[ K_l = \frac{N_l}{N}. \]

The distortion coefficient is defined as the ratio of missing and non-interpretable clusters to their total number

\[ K_d = \frac{(N_i + N_{ni})}{N}. \]

The coefficient of interpretability for distorted objects is defined as the ratio of interpretable distorted clusters to the number of interpretable and non-interpretable distorted clusters.

\[ K_{int} = \frac{N_i}{(N_i + N_{ni})}. \]

The coefficient of representativeness is defined as the ratio of undistorted clusters to the total number of clusters

\[ K = \frac{N_o}{N}. \]
The coefficient of informativeness is defined as the ratio of non-interpretable clusters to the total number of clusters

\[ K_{\text{inf}} = \frac{(N_I + N_0)}{N}. \]

It can be said that, with this approach, informativeness is associated with interpretability and the number of interpretable clusters. In this approach, informativeness is calculated using not one indicator but several.

4. Conclusion

The approach to the informativeness evaluation using entropy should be considered incomplete or inconsistent. The entropy is evaluated by the information volume in bits, the number of which does not change for the carriers of scanned digital images, both in the presence of an informative image and in its absence. It is advisable to evaluate the informativeness by visual clusters that have the property of integrity and contain a certain integral semantics [21]. The informativeness of visual models should be evaluated by semantically meaningful components, including not only clusters but also their image structure. This article does not solve all the problems of the informativeness evaluation. It shows an approach based on a set of key indicators to describe this complex phenomenon. Cognitive semantics can be the next step in the analysis since each cluster, relation and background can have a designation and meaning. I.e., the connection of the Frege triangle for analysis makes the simple model in expression (1) multidimensional but more complete in terms of the informativeness evaluation. This direction is the subject of the following researches.

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