Visual detection of internal patterns in the empirical data

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Abstract. The article proposes the solution of the problem of the multidimensional data research. The purpose of such research is detection of internal regularities in initial data, what increases the level of knowledge and understanding the essence by the researcher.
The possibilities of using visual data models to achieve this goals are shown. Results of practical use of visual analysis of multidimensional data for justification of the choice of not determined parameters for modeling and designing oil and gas fields using given analogies. High productivity of the developed approach for solving problems of the multidimensional data analysis was confirmed.

Keywords: Cognitive graphics; Computer visualization; Decision supporting systems; Dynamic visualization; Interpretation; Visual interpretation; Visual model; Visual perception

1. Tasks of data analysis

In a case when the user has an experience in using visual models, actual grounds appear for explanation their effectiveness and a choice of the most effective tool [1]. Due to this, there might be an additional advantage of visual analysis, related to the reduction of time. First of all, to select the type of visual model it is necessary for the researcher to understand accurately the goal for using visual analysis tools.

The purpose of data analyses, including visual data, is to obtain an answer of the main research question [2]. While constructing a general analysis methodology, two additional circumstances should be considered. Firstly, before the completion of the analysis process, new data appears which may affect on the formulation of the main question. Secondly, the answer for the question should be considered not as the state of the visual model, but the achievement of the researcher of the necessary degree of understanding of this state.

Therefore, the meaning of the research issue, the validity of the formulation, the degree of its complexity, the correspondence between the form of the response obtained as a result of interaction with the model and the researcher's understanding of its significance become important [3]. Since getting the right idea about the result of the analysis is a priority task of the visual model, the development of expressive tools (which are a part of the visual model) need to focus on this circumstance, and not, for example, on the correspondence to the initial data.

In addition to understanding the goal, there are numbers of additional circumstances which increase the effectiveness of the process of visual analysis. There is the factor of emotional persuasiveness that allows the user to make a decision without the need for excessive verification of its reliability, as well as the ability to overcome the negative impact of such factors as a lack of concentration, fatigue or subjective rejection.

Differences in purposes of analysis form several types of models.

- **Analytical models.** Designed to find unknown patterns in the data, internal dependencies, correlation of changes in parameters, etc.
- **Controlling models.** They are used to detect inconsistencies in the visualized information to the existing understanding, inaccuracy or insufficiency of data that could not be seen or estimated by other tools.
- **Models of choice.** Are focused on granting methods of a comparison of possible variants of decisions to the researcher in those problems when the necessary choice is made by expert opinion using internal knowledge of the user or other criteria chosen by him.

2. Requirements for the visual solution

Solving the problem of visual analysis of data leads to obtaining new information that can have a reverse effect on the user's opinion, and therefore there are a number of requirements for the procedure for obtaining an answer of the research question. For example, the features of using visual models are associated with the concentration of attention on the object of studies [4]. This leads to the need for simultaneous visualization of both the background information and the intermediate information needed to answer the research question.

Changing the visual model during the analysis of the data creates the need to verify the correspondence of the new shape to the conditions of the initial analysis task. The phase of such assay also becomes a part of the visual image and changes its perception [5]. The output from an infinite cycle of verification of the received solutions is achieved by means of the visual model itself. For this purpose, the following characteristics have been distinguished:

- Predictability of the consequences of decision making.
- Compliance with additional criteria.
- The uniqueness or originality of the solution [6].
- Dimensionless of the representation.

3. Complex approach to visual analysis

Visualization is one of the ways of modeling and it fulfills functions of the cognitive tool. While creating a visual image of the studied data, the original object S is associated with the model Z, which can have a completely different ontological affiliation. As an object of study, S can be a real object or a complex of them, data of any kind and origin, events, as well as individual properties of P_i objects. Thus, the object of the research $S = \{P^{(S)}_i\}$ is considered to be a set of elements localized in time (t) and space (r). The visual model Z is also an object, which consists of properties of $P^{(Z)}_k$, which are matched to the original [4].

$$S(t, r)= \{P^{(S)}_n(t, r)\} \rightarrow Z(t, r)=\{P^{(Z)}_k(t, r)\}, \ n = 1..N(S),\ k = 1..K(Z),$$

where N(S) is the space dimensionality of features of the original object S; K(Z) is the number of perceived characteristics of the visual model associated with the original object.

In general, the dimensions of spaces of features N (S) and K (Z) may not be coincided. In addition, some properties of the object N*(S) are not correlated to properties of the model Z. Such models - Z_A are abstract, because the choice of displayed properties is arbitrary and is determined by the author of the visual model. Any visual model is abstract:

$$Z_A = \{P^{(Z)}_k(t, r)\} \mid F_{map}: P^{(S)}_{N(S)} \rightarrow P^{(Z)}_{K(Z)},\ P^{(S)}_{N^*(S)} \rightarrow\!\mid P^{(Z)}\}$$

The visual image received by the observer is an artificial form, located between sensual perception and thinking. This allows to combine visual processing of information and mental analysis of data stored in the memory of the researcher. The rationale of choosing the matching method (modeling function) F_{map} is necessary to create the most successful simulation analogy, ensuring success of visual analysis. The purpose of visual analysis is to obtain an answer for a question with a visual model, within the constraints.

The statement. The effectiveness of visual analysis increases in the case of implementation of a complex approach in the function of visual modeling.

The decision to choose a matching method is taken by the author of the model. Subjectivity of the model and its interpretation determines the existence of objective $R_{map}(S)$ and conventional $C_{map}(S)$ components in the modeling function F_{map}. For abstract models Z_A, the conventional matching function of $C_{map}(S)$ becomes the main function.

$$F_{map} = \{R_{map}(S), C_{map}(S)\};$$

$$Z_A = \{P^{(A)}_k(t, r)\} \mid F^{(A)}_{map}: C_{map}(S)=\max, R_{map}(S)=\min\}$$

Thus, the choice of the mapping function (visual modeling) depends on properties of the original object S, the goal of modeling E_v and the subjective decision of the researcher H. Each of the arguments of the visual modeling function can vary in space and time.

$$C_{map} = C_{map}(S, r, t, E_v, H)$$

Subjectivity influences on the solution of the task of visual analysis twice: from the side of the author of the model and from the side of the researcher. Therefore, the control of the effectiveness of visual analysis should include management of the visual presentation of the data and management of its reading. This creates two additional components in the simulation function: the direct function E_{pr} (control of the presentation form, representation) and the inverse one E_{it} (control of the results of perception, interpretation).

$$C_{map} = \langle C_{map}(E_v), C_{map}(E_{pr}), C_{map}(E_{it}) \rangle$$

Corollary A. Each component of the modeling function can be controlled and changed in time.

Corollary B. Regulation of the degree of participation of each component leads to the creation of visual models for various purposes and allows to solve problems of visual analysis of different types.

Corollary C. The effectiveness of visual analysis is determined by the time taken to obtain a solution.

Based on the proposed idea of the participation of various factors in solving problems of visual analysis, there are several definitions:

An integrated approach (to visual data analysis) is a balanced directional use of all components significant for achieving the purpose of analysis in the function of visual modeling C_{map}.

Functional approach C_{map} (E_v). The visual modeling function is responsible for matching visual data to objects based on the purpose of the analysis - E_v. Tasks of the functional approach are decomposition of the main question of analysis into research stages which have controlled effectiveness. Examples of such steps are answers for basic questions, the formulation of intermediate tasks, preservation of the research data or connection to the analysis of additional data sources.

Semiotic approach C_{map} (E_{pr}) is a function of representation of the data, aimed at choosing the form of presentation, depending on the type and amount of data, available modeling resources, observer's awareness. The task of the presentation function C_{map} (E_{pr}) is the transfer of data to the stage of thinking in a form that ensures the achievement of the goal or corresponding to the formulated requirements. The generalization of modeling tools, which is necessary for the presentation of various data, is the basis for the transition to the concept of visual language [7].

The psychoemotional approach C_{map} (E_{it}) is a modeling function which regulates the interpretation of the visual shape [8]. It is necessary to overcome or exploit the subjective nature of visual perception. The main tasks of the interpretation function $C_{map}(E_{it})$ are the use of the cognitive potential of the researcher, managing his motivation and attitude to the analysis, reducing the time spent on making a decision.

4. The structure of the visual model of data

Data analysis is a process directed by an action which can be a sequence started with the formulation of the question and continued with the search for hypotheses contained the answer for this question. In this case, the correctness of the result of the analysis depends on two factors: the nature of the issue, which is determined by the degree of preliminary understanding of the analyzed information, and also the form of the question (see Fig. 1). The form is determined by the language of the question, by the internal structure, by logic and need for interaction with additional sources of information [9].

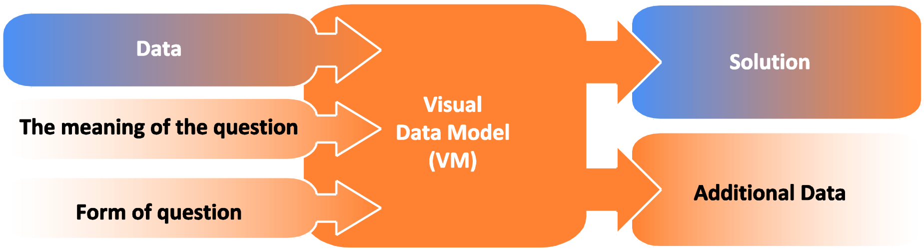

Fig. 1. Analysis of the visual shape.

The scheme of the visual analysis process, demonstrated a consistent approach to the answer on the general research question (see Fig. 2), confirms the reasonableness of the integrated approach to the visual analysis. The modeling functions, combined in an integrated approach, are parallel information flows that regulate the process of analysis.

Statement. Visual data analysis is a controlled process of constructing the pattern of regularities discovered by the user in the data.

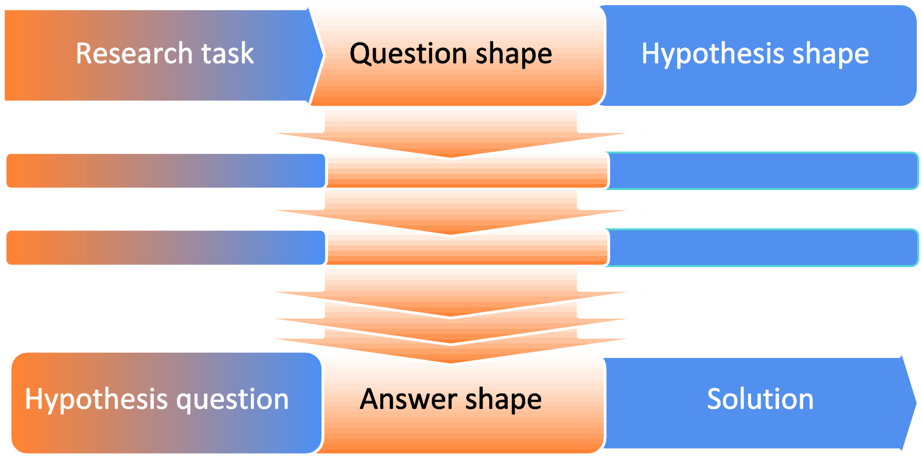

Fig. 2. The scheme of functioning of the visual model.

Corollary A. The visual model should allow verification of regularities which are the result of the analysis.

Corollary B. The consistent nature of the analysis process allows dividing the whole process into stages which have the same properties and purpose.

The structural unit of visual analysis is an element of the visual model (see Fig. 3). The visual element is the state of the visual model, interpreted as a response to an elementary question, previously deliberated by the user. The complexity of such question is determined by the limited time of the analysis.

The structural unit of the visual analysis is a controlled system S with feedback R(t). The volume of the studied data comes in to the uncontrolled input V(t) of the structural unit. A feature of such system is the possibility of changing the state of the controlled input of the system U(t) as a function of the obtained results Y(t). User P is a mandatory participant in the structural unit, from the point of view of an integrated approach to the visual analysis.

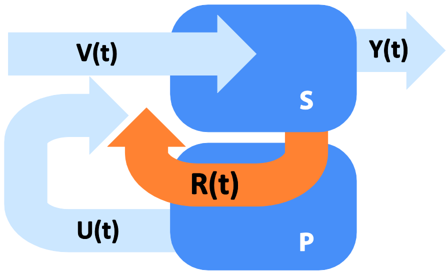

Fig. 3. Structural unit of visual analysis.

In general, the element of the visual model can be represented by a simple logic scheme (see Fig. 4). The tested data is going to the unmanaged input (IN), forming the original form. As a result of user's interaction with the form, a new form is formed, corresponding not to the original data, but to the understanding of their meaning by the researcher. It corresponds to the amount of new data sent to the output (OUT). If the received information is a necessary response, then the analysis process ends, and in the remaining cases the data is transferred to the input of the next element of the visual model.

In the process of forming the response, a request is made to attract additional information which is sent to the controlled input (IN2). In addition, the comprehension even of a single visual fact can create associative hypotheses which are answers to questions that are not relevant to the topic of the research. These data can be captured in the form of perceived fragments of the data shape and be memorized by the user. It enters the output of the structural unit, (OUT2) and changes its own internal awareness.

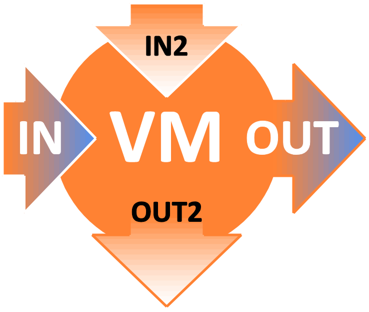

Fig. 4. Logical diagram of the structural unit.

Based on the proposed description of the structural unit of the visual model, it becomes possible to accurately determine types of visual models which differ in their capabilities, purpose and, therefore, applicability for solving various types of problems. The logical schema of the element allows to declare differences between them based on the activity of using existing links. In addition, the combination of structural units, including various types, allows analyzing and predicting the effectiveness of using visual analysis tools.

5. Selection of the type of the visual model

Attraction of visual research methods is aimed at reducing the time spent on data analysis. A preliminary study of possibilities of the visual model makes it possible to determine its correspondence to conditions of analysis and, possibly, to eliminate elements that require unreasonably long time expenditure. In addition, from the point of view of an integrated approach, the basis for choosing a visual model is, not only the features of the problem being solved, but also the characteristics of the researcher [5].

Based on the proposed description of the structural unit of visual analysis, the visual model can be determined by the characteristics of the activity of using information's inputs and outputs. In one of the simplest cases, the visual image is used as an indicator of the state of the observed system. The purpose of the data model is to notify the observer about a change in state or, more correctly, about the occurrence of an expected event (see Fig. 5).

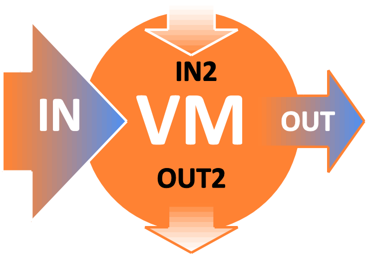

Fig. 5. Model of visual information.

The main load is tested by the information input (IN), which provides modeling functions with information about the necessary form of informing of the observer. This means that no information is important for the user, except the message about the occurrence of the expected state (OUT). Input of additional information (IN2) is not activated, because the expected shape is the part of the conventional notation system. Consequently, increasing the effectiveness while solving the problem of analysis of this type is associated with the maximum simplification of the visual shape.

In addition, the control effect, formalized as a question to the stage of visual analysis (IN2), in this case is transformed into the simplest logical switching "yes / no?". The control action (OUT2), associated with a visual assessment of the shape and the appeared emotional response, can also be reduced as much as possible, because of the use of unambiguously interpreted shapes. Thus, the transition to the next stage of visual analysis, if it exists, occurs together with a change in the state of the user's internal awareness. It arises as a realized expectation, which does not use external sources of information and does not change the amount of accumulated knowledge.

In the following case, the use of external connections of the structural element of the visual model takes more complex character. A new visual model is designed for user's training, i.e. for information, accompanied by the verification of a new solution due to the previously generated internal awareness of the user. In a simplified form, the task of the training visual model is to transmit to the observer the necessary amount of information, which reliability is not questioned (see Fig. 6).

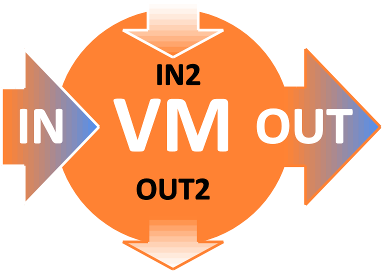

Fig. 6. Visual model of training type.

The verification of the hypothesis of interpretation occurs on the basis of previously defined criteria for achieving the necessary degree of understanding and becomes a formalized procedure. As a result, a training model or a visual model, intended for the most correct transmission of information, must have powerful information links - both incoming (IN) and outgoing (OUT), while the role of control links (IN2, OUT2) can be reduced to Minimum functional purpose.

Visual data models are widely used in decision support systems. In this case, the analysis task requires a quick comprehension of the incoming data. The determining condition for data models is the active use of the observer's knowledge and experience to obtain conclusions that influence on the further existence of the system [10]. This type of visual analysis is characterized by the active use of additional information, user's knowledge and the formulation of interim questions (see Fig. 7).

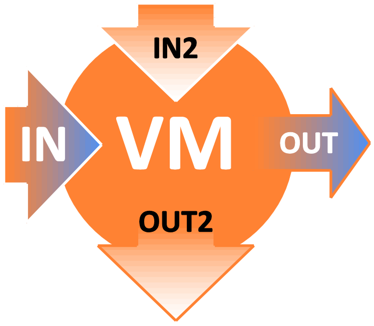

Fig. 7. Visual model for decision-making tasks.

The model's information input (IN) is used to provide the information which is necessary to construct a visual image in a form consistent with the form of the control question, which enters the input (IN2). This means that the perceived components of the model become objects that initiate the construction of response hypotheses, and therefore the choice of the type of visual representation has fundamental importance [11].

6. The task of data recovery

Due to the high speed of data analysis with the help of visual models, their application in the study of empirical data, which require a large amount of computation or mental efforts, is in demand. Evaluation of the effectiveness of the use of visual methods of data analysis was held for reconstruction the missing data in the description of oil production facilities. Objects of analysis are parameters (geological, technological and other) of the oil and gas field, which are necessary for designing, modeling forecasting solutions, estimating reserves, etc. In this case, all parameters are characterized by a high cost of obtaining and not all of them are measured or identified. The hypothesis of solving this problem is the assumption of the possibility of borrowing missing data from deposits characterized by similar geological conditions, similar values of key parameters. Thus, the purpose of visual analysis is to quickly find objects that have similar properties. The proximity criterion is determined by the user subjectively (based on the expert's judgment).

While designing the development of deposits, the search procedure for analogies is poorly formalized and in many ways is subjective - the decision always remains for the designer or expert and is often based on personal experience and is not supported by factual material. Thus, the peculiarities of the considered problem are analogies:

- Diversity of data;
- Lack of strict formalization and methods of solution;
- Subjectivity of the received solution (Weighting factors of the parameters are determined by the expert);
- Flexible restrictions constraints (in the absence of a solution, the framework can be extended to increase the sample being processed, since the solution must be found in any case).

Traditionally, the solution of the problem of selecting analogies can be obtained statistically, this method is associated with processing of tabular data on available deposits and identifying objects that are close by certain criteria. The visual solution of the problem can be obtained using histograms of deviations, correlation diagrams, etc. (see Fig. 8), which is time consuming, because In this case, the expert must analyze graphs for each parameter. In this issue, to search for a solution, there is a need to construct diagrams with 13 parameters (n = 13).

Indicated solutions are associated with the processing of large amounts of data, are time-consuming and do not allow a comprehensive assessment of all available data in one model, which would make shorter the decision time. The main reason for this is that in modern conditions of growth of information volumes, traditional methods of visual data analysis based on flat two-dimensional models can not provide sufficient information to the user. It is necessary to use multidimensional data models [12].

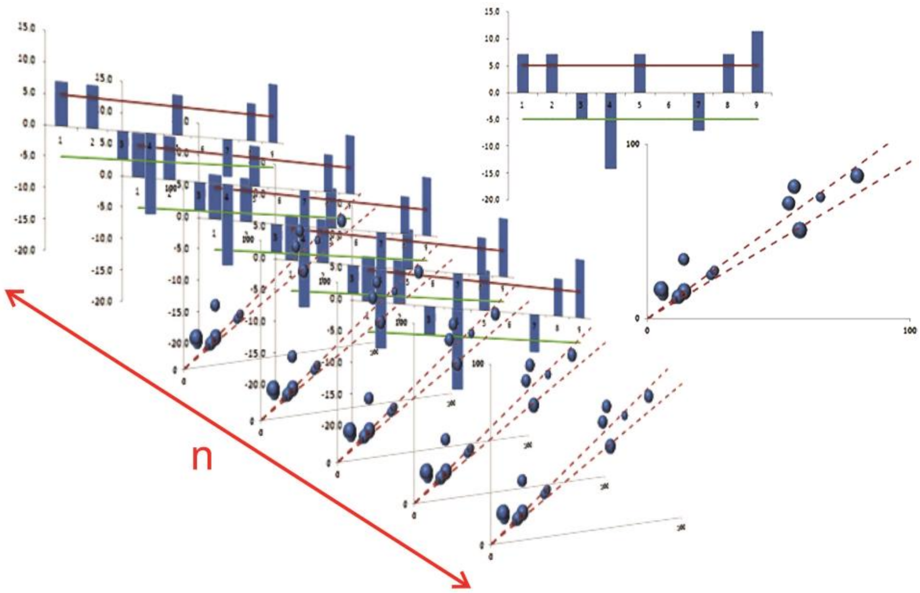

Fig. 8. Visual solution of the problem of choosing analogies in the traditional way.

To solve any problem, a model, corresponded to the type of visual decision making, is required. This indicates on the need to actively engage the user's capabilities in obtaining an answer to the research question. In addition, one of the prerequisites is to reduce the analysis time. The fulfillment of this requirement can be achieved by simplifying the model to the type corresponded to the usual information, as well as by using expressive visual means that do not require long acquaintance and reflection (Table 1).

The function C_{map} (E_{pr}) is to reduce the time required for the user to get acquainted with the original data. In the situation of visualizing a significant number of parameters, C_{map} (E_{pr}) is selected to remove components that require familiarization from the shape being created. For this reason, in the model being created, the shape of an individual element, combined a given number of parameters, is represented as a three-dimensional graph.

Table 1. An example of a data structure that is examined according to the principle of analogies.

Name		Weight (1-5)	Tolerance,%	Unit of measurement	Conditions
Poro	Porosity	5	10	Unit fraction	0,1 < Poro < 0,25
So	Oil saturation	5	10	Unit fraction	0,4 < So < 0,7
Perm	Permeability	5	10	mkm^2	0,1 < Perm < 30
m_o	Oil viscosity in reservoir conditions	4	15	мPa*s	$m_o < 1,2$
ρ_o	Oil density in surface conditions	4	8	g/cm^3	$0,8 < \rho_o < 0,95$
b_o	Oil-formation volume factor	4	5	Unit fraction	$1,1 < b_o < 1,3$
G	Gas content of in-place oil	4	10	$м^3/t$	30 < G < 150
h	Average net productive formation thickness	3	20	м	2 < h < 47
h_{net}	Average net oil thickness	3	15	м	$0,5 < h_{net} < 31$
H	Average depth of bedding	2	5	м	2350 < < 2590
NTG	Net-to gross	2	15	Unit fraction	0,42 < < 0,76
p	Initial formation pressure	2	15	MPa	19 < p < 27
ρ_w	Water density in surface conditions	1	5	g/cm^3	$1,005 < \rho_w < 1,150$

One of ways to solve the problem of effective time use is to reduce the amount of excessive information for an observer. On the one hand, this is achieved by analyzing the informativeness of the obtained images and eliminating elements whose meaning is not related to the formulation of the study. But, in addition, it is possible to involve the ability of a person to mental interpolation and extrapolation of data, which makes it reasonable to reproduce in the data model only a part of them [13].

The organization of the verification procedure, performed by the interpretation function C_{map} (E_{it}), for models with the need for deep decomposition of the original question, is a complex problem. Therefore, in the studied issue, the visual model is accompanied by the maximum possible degree of interactivity of the control system (see Fig. 9), which allows to formulate a mental question at each step of the analysis in such a way that it corresponds to the speed and features of the researcher's thinking.

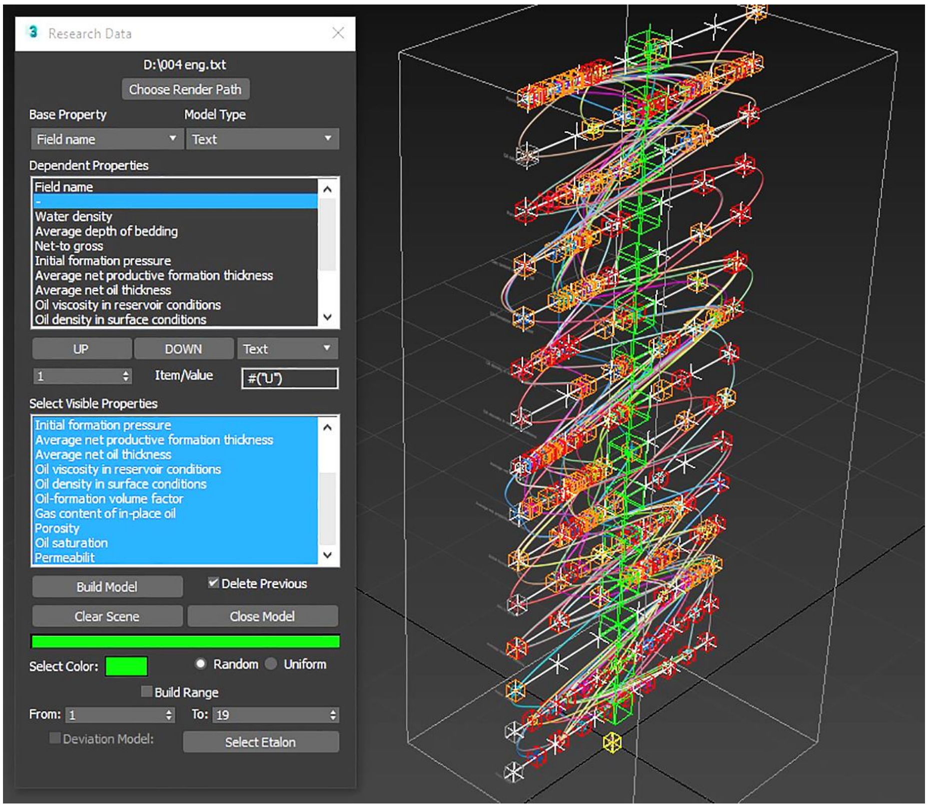

Fig. 9. Interface of the developed visual data model.

In addition to evaluating an array of heterogeneous data in one visual model, the complexity is also in the ability to perform visual analysis of data simultaneously in several directions: absolute values, absolute and relative deviations from the standard, and data dynamics.

Within the framework of this search for analogies, the closest analogue field is selected from the sample of candidates, taking into account the weight coefficients of parameters and permissible deviations of parameters of candidates from the standard.

A conceptual diagram of the obtained visual data model for solving the problem of searching for analogies in the design of field development is presented in Fig. 10.

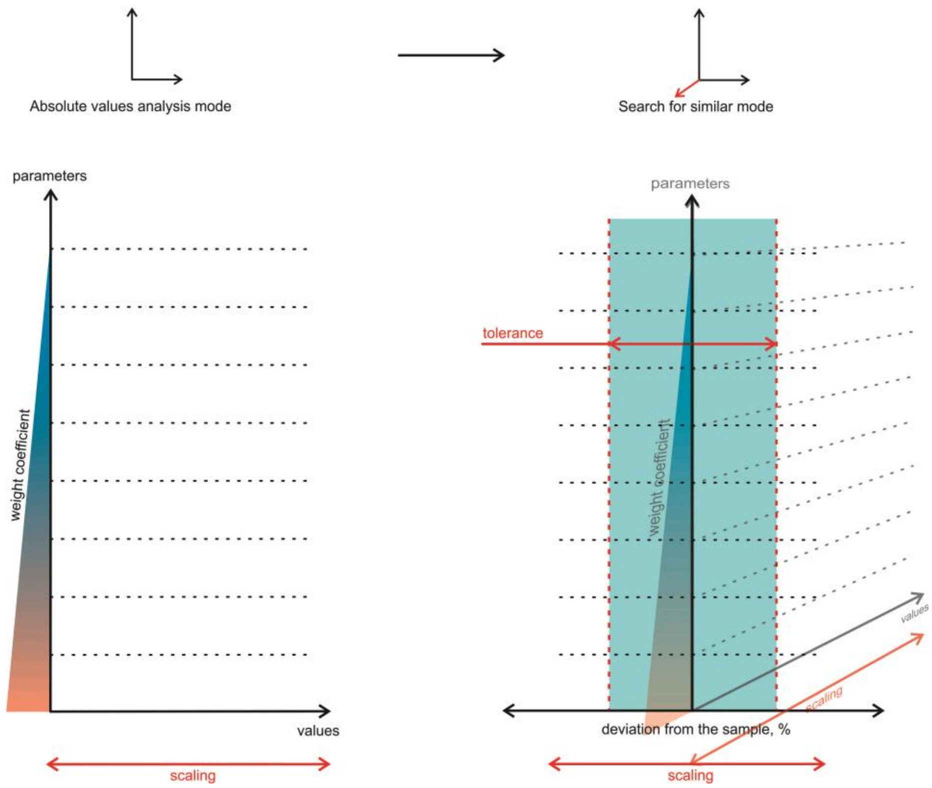

Fig. 10. Conceptual diagram of the visual data model.

In 2D mode the model allows to analyze the array of data taking into account the weight coefficients, while for a better visual perception, parameters are scaled. To solve the problem of finding analogies in the model, the comparison mode with the standard is implemented, for which a third dimension is added, which displays the deviation of parameters of each candidate from the standard. The solution of the problem is reduced to a visual assessment by the expert of deviations of parameters and the choice of the most suitable candidate.

To test the presented approach on real data, one of the Tomsk Oblast deposits was selected, where there are no own core studies which are necessary for designing the development forecast. Such studies can be taken on a similar deposit, it is necessary to find in the initial sample of candidates an analog field that is closest to the benchmark by key parameters. The initial sample includes 18 candidates (see Fig. 11). Of the total data set for each of the deposits, 13 (n = 13) key geological and physical characteristics were assigned. Weight coefficients and allowable deviations from the standard were appointed to them. The resulting visual model is shown in Fig. 12

Parameters	Weight (1-5)	Tolerance, %	Sample M1	M2
Water density	1	+5, -5	1,02	1,027
Average depth of bedding	2	+5, -5	-2406,5	-2478
Net-to gross	2	+15, -15	0,66	0,52
Initial formation pressure	2	+15, -15	25,5	25,3
Average net productive formation thickness	3	+20, -20	13,8	12,6
Average net oil thickness	3	+15, -15	6	4,8
Oil viscosity in reservoir conditions	4	+15, -15	0,56	0,61
Oil density in surface conditions	4	+8, -8	0,799	0,808
Oil-formation volume factor	4	+5, -5	1,178	1,229
Gas content of in-place oil	4	+10, -10	54	71,4
Porosity	5	+10, -10	0,14	0,15
Oil saturation	5	+10, -10	0,58	0,65
Permeability	5	+10, -10	0,0051	0,005

Candidates	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19
Water density	1,001	1,024	1,025	1,023	1,02	1,02	1,026	1,027	1,02	1,02	1,02	1,024	1,024	1,026	1,026	1,025	1,025
Average depth of bedding	-2467	-2689	-2337	-2463	-2481	-2500,1	[illegible]	[illegible]	-2100	-2149	-2189	-2380	-2386	-3066	-3069	-2875	-2877
Net-to gross	0,69	0,49	0,4	0,55	0,82	0,8	0,76	0,49	0,49	0,6		0,91	0,72	0,78	0,82	0,8	0,65
Initial formation pressure											22,1	24,7	24,7	35,6	35,6	31,1	28,12
Average net productive formation thickness											17,1	3,1	20,6	10,4	6,3	61,3	48,8
Average net oil thickness											4,5	2,5	7,3	3,8	5,7	19,5	15,2
Oil viscosity in reservoir conditions											1,02	1,02	1,02	0,43	0,43	0,91	0,6
Oil density in surface conditions											0,812	0,812	0,812	0,79	0,79	0,797	0,794
Oil-formation volume factor											1,105	1,105	1,105	1,501	1,501	1,25	1,286
Gas content of in-place oil											28,7	28,7	28,7	186,7	186,7	102,1	110
Porosity											0,23	0,19	0,201	0,098	0,11	0,13	0,13
Oil saturation											0,6	0,46	0,51	0,59	0,68	0,59	0,59
Permeability											0,03	0,004	0,006	0,008	0,007	0,001	0,002

Fig. 11. Initial sample for finding analogies.

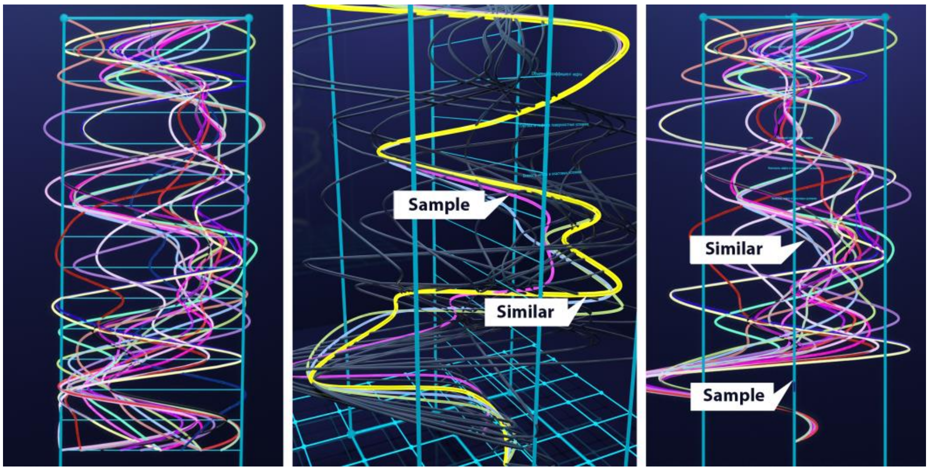

Fig. 12. Visual data model for the task of finding analogies among deposits.

The created tool for visual analysis and obtaining new information is an example of visual data interpolation due to the realization in the model of the functional principle of visual analogies. Using the developed visual model allows to identify quickly in the studied empirical data objects, which are close to each other, in terms of the observer and the principles recognized by him. This approach allows you to quickly and efficiently evaluate, analyze and compare large amounts of data, which is time-consuming when using traditional methods of analysis [14].

In addition, such model allows to verify the data, as well as assessing the obtained forecast solution for field development, taking into account the experience of developing similar facilities (see Fig. 13).

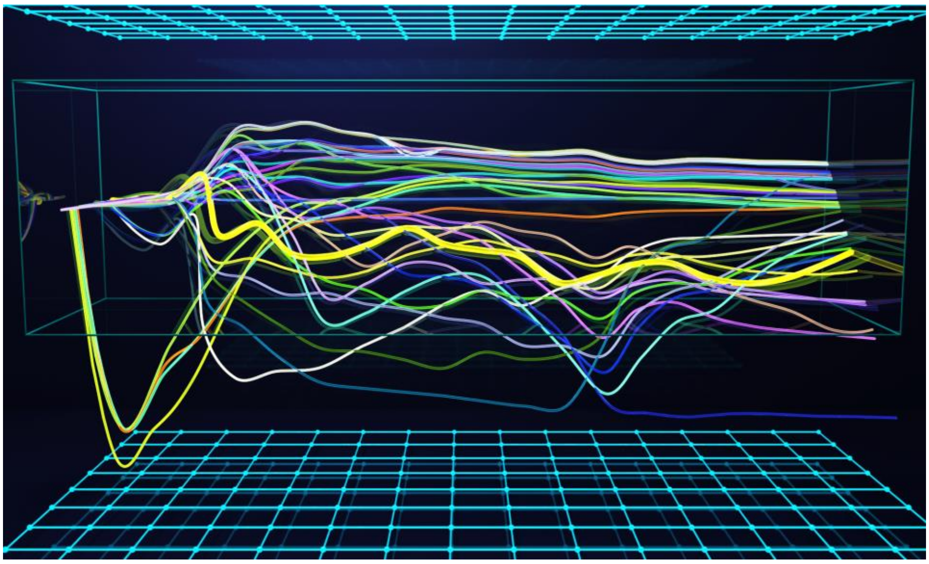

Fig. 13. Example of an estimate of the forecast solution taking into account the development experience.

The use of visual models adapted to rapid transformation, controlled and justified from the point of view of the impact on the observer, develops the definition of the process of visual analysis. In this case, visual analysis becomes a consistent process of investigating some information, and consists in a meaningful manipulation of the visual model. The goal of such controlled transformation is a step-by-step transition to a visual model, which interpretation is analogous to the formulated answer to the general question of analysis.

7. Conclusion

Application of visual methods of the data research allows to use the researcher's knowledge in creating a solution hypothesis. The creation and description of the visual, based on the proposed integrated approach, made it possible to identify main ways to increase the effectiveness of the multi scale analysis of multidimensional data. Recusing the time of the analysis of such data is reached using interactive management of a visual shape. The offered approach of the data analysis is used to solve a problem about justifying the choice of not determined parameters for modeling and designing oil and gas fields using given analogies. This is the first time when in one visual model multidimensional and multi scale data have been comprehensively evaluated. Therefore optimum parameters of modeling a field have been selected.

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References

1. Chen, C.: Mapping Scientific Frontiers: The Quest for Knowledge Visualization. 2nd ed. London: Springer, (2013).
2. Korobkin D., Fomenkov S., Kravets A., Kolesnikov S., Dykov M.: Three-Steps Methodology for Patents Prior-Art Retrieval and Structured Physical Knowledge Extracting. In: Creativity in Intelligent Technologies and Data Science First Conference, CIT&DS 2015, pp.124-138. Volgograd, Russia (2015).
3. Bondarev, A.E., Galaktionov, V.A.: Multidimensional data analysis and visualization for time-dependent CFD problems. Programming and Computer Software 41(5), 247–252 (2015). DOI: 10.1134/S0361768815050023.
4. Solovyev, R., Seryakov, V.A.: Advertisements and information objects positioning technologies based on the territorial zoning of the city of Tomsk. IOP Conference Series: Materials Science and Engineering 2014, vol. 66: 20th International Conference for Students and Young Scientists: Modern Techniques and Technologies, Tomsk, Russia, (2014).
5. Zakharova, A.A., Shklyar, A.V.: Visual presentation of different types of data by dynamic sign structures. Scientific Visualization 8(4), 28-37 (2016).
6. Chen C.: Top 10 unsolved information visualization problems. IEEE Computer Graphics and Applications 25(4), 12–16 (2005).
7. Averbukh, V.: Semiotic Approach to Forming the Theory of Computer Visualization [Semioticheskij podhod k formirovaniju teorii komp'juternoj vizualizacii]. Scientific Visualization 5(1), 1-25 (2013).
8. Sedig Kamran, Parsons Paul, Hai-Ning Liang, Jim Morey: Supporting Sensemaking of Complex Objects with Visualizations. Visibility and Complementarity of Interactions, Informatics 3(4), 20 (2016). doi:10.3390/informatics3040020.
9. Eppler, M., Burkhard, R.A.: Visual representations in knowledge management: Framework and cases. Journal of Knowledge Management, vol. 11(4), pp. 112-122. QEmerald Group Publishing Limited (2007). ISSN 1367-3270 DOI 10.1108/1367327071076275.
10. Shneiderman, B., Plaisant, C., Cohen, M.S., Jacobs, S.M., Elmqvist, N., Diakopoulos, N.: Designing the User Interface: Strategies for Effective Human-Computer Interaction. 6th ed. Pearson: Upper Saddle River, NJ, USA (2016).
11. Huang, D., Tory, M., Adriel Aseniero, B., Bartram, L., Bateman, S., Carpendale, S., Tang, A., Woodbury, R.: Personal visualization and personal visual analytics. IEEE Trans. Vis. Comput. Graph. 21, 420–433 (2015).
12. Ozpeynirci, O., Ozpeynirci, S., Kaya, A.: An interactive approach for multiple criteria selection problem. Computers and Operations Research 78, 154-162 (2016).
13. Zavyalov, D.A., Zakharova, A.A., Shklyar, A.V., Bagutdinov, R.A.: An integrated approach to modeling by an example of a landfill of disposal of liquid oil waste. Software systems and computational methods [Programmnye sistemy i vychislitel'nye metody] 1, 22-30 (2017).
14. Zaripova V.M., Petrova I. Yu., Kravets A., Evdoshenko O.: Knowledge Bases of Physical Effects and Phenomena for Method of Energy-Informational Models by Means of Ontologies. In: Creativity in Intelligent Technologies and Data Science First Conference, CIT&DS 2015, pp. 224-237. Volgograd, Russia (2015).