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ESTIMATING INFORMATIONAL CONTENT IN GEOPHYSICAL OBSERVATIONS ON EXAMPLE OF SEARCHING ECONOMIC MINERALS IN AZERBAIJAN

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The application of geophysical methods to searching useful minerals is usually limited by physical, geological, economic and time considerations. The presence of numerous kinds of noise means that in many cases the anomalous targets (ore bodies, hydrocarbon pools, etc.) and surrounding media are best approached as probabilistic objects, such that the amount of information potentially available from different geophysical methods can be estimated by probabilistic and statistical methods, including the risks associated with this decision making. Here it is shown that simple informational and probabilistic criteria can be applied to formalize the information that can be obtained by applying different geophysical methods. To assess the relative value of geophysical methods, information, cost and time factors are convoluted to generate integrated parameters. Calculation of some information parameters in the regional scale in the South Caspian Basin, and in the local areas: Bulla Deniz gas deposit (offshore Azerbaijan), and Gyzyl-Bulakh gold-pyrite deposit (Lesser Caucasus, western Azerbaijan) shows an effectiveness of this methodology.

INTRODUCTION

It is well-known that majority of the inverse problem solutions in geophysics are ill-posed (e.g., Zhdanov, 2002). It means that the solution does not exist, or is not unique, or is not a continuous function of observed geophysical data (when small perturbation in the observations will cause arbitrary mistake in the solution). This fact, in particular, calls to wide application of informational and probabilistic methodologies in applied geophysics and geology.

Geophysical observations in searching useful minerals are notoriously complicated by numerous factors. To eliminate many of these disturbances numerous interpretational methodologies have been developed (Khesin et al., 1996). However, at times the complexity of the geological environment (variability in lateral and vertical physical properties), large depth of anomalous targets (**AT**) occurrence and additional disturbances makes it impossible or unfeasible to apply these methodologies. In such cases information-probabilistic methods are effective tools to recognize and classify targets (e.g., Duda and Hart, 1973), estimate the potential information value of geophysical methods and decide upon a workable solution. The objective of geophysical surveys is to obtain qualitative and quantitative information about the geometric and physical characteristics of buried **AT**; e.g., to develop physical-geological models (***PGM***) of target objects. ***PGM***s of varying degrees of complexity (the simplest ***PGM***s are purely target identification and complex ***PGM***s can be 3D models of buried **AT**) can be used to justify drilling (excavations) in defined areas and generate future strategies for geophysical-geological searches in areas where **AT** are known to exist.

This article gives a very short description of some of the key features of the informational approach to geophysical methods applied for searching useful minerals. Here it is shown that simple informational and probabilistic criteria can be applied to formalize the relative value of geophysical methods, geophysical information, cost and time factors to generate integrated parameters.

Estimating the information value of geophysical, geochemical and other means can be formalized on the basis of the following criteria (after Eppelbaum et al., 2003) (Figure 1):

(1) Informativeness of the application (informational criterion Γ);

(2) Cost of implementing the method (cost criterion C);

(3) Time required to carry out the method (time criterion T).

Criteria C and T are easy to calculate directly, but criterion Γ is a non-trivial research problem. A simplified algorithm can be written as:

$$\Omega = \Gamma \cup C \cup T, \qquad (1)$$

where $\cup$ is the symbol of unification.

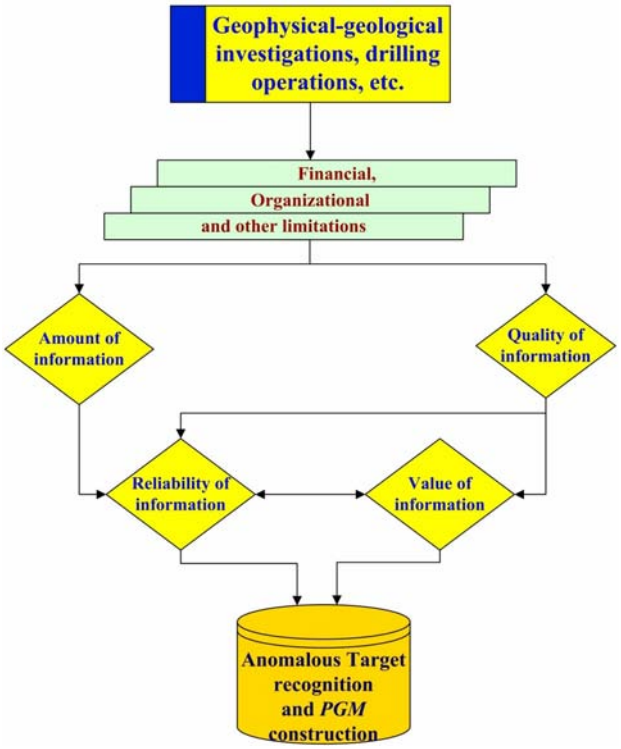


Figure 1. A scheme of anomalous target recognition and ***PGM*** construction with elements of information theory

All the available geological information can be represented as the classic three-level model (Figure 1): (a) syntactic – quantity of information, (b) semantic – content of information, and (c) pragmatic – value of information. The logical-heuristic model for describing environmental information thus takes the following form (Eppelbaum et al., 2003):

$$\Gamma = I \cup R \cup V, \qquad (2)$$

where I is the quantitative estimation of information, R is the estimation of informational reliability corresponding to the semantic criterion, and V is the estimation of informational value in terms of feasibility according to the pragmatic criterion.

Algorithm (2) is based on the fundamental terms of information theory and is combined with the structural (hierarchical) approach. This approach defines each indicator as a structure reflecting a set of typical situations and is then used to calculate the value of each estimator using the informational measure. Parameters V and R should be estimated geologically, but this is beyond the scope of this paper. Here parameters V and R will be neglected, and it is assumed that $\Gamma = I$.

A variant of the possible analysis of geological-geophysical information is presented in Figure 2.

EVALUATING THE EFFICIENCY OF GEOPHYSICAL METHODS WITH INFORMATIONAL-STATISTICAL PROCEDURES

General considerations

Choosing the right method (or number of methods) can be based on a qualitative-quantitative estimate (Figures 1 and 2). For this purpose, reliable informational and statistical criteria are needed. The first issue is the quantity of information that can be obtained by a single method or a set of methods (geophysical, geochemical and other data). The second is to define a criterion to express the decision-making risk as a function of the obtained data. Nevertheless, informational criteria are preferable, because geological-geophysical prospecting is a permanent process of acquisition and analysis of different kinds of information.

The classic information theoretic works by Shannon (1948) and Brillouin (1962) prompted Khalfin (1958) to apply firstly these criteria to geology and geophysics. It has been shown (Khesin et al., 1996) that informational and statistical approaches represent two aspects of a shared approach. For instance, the solution to an identification problem using the criterion of minimal average risk or that of maximum information (minimal residual uncertainty) under definite conditions results in the same expressions (Svetov, 1992; Nikitin, 1993). An enhanced wavelet approach to integration of geophysical data under complex geological conditions was proposed by Eppelbaum et al. (2011). In many cases this approach is similar to enhanced information method.

This lays the groundwork for presenting some of the key elements of the theory of information and statistical-probabilistic approaches in prospecting of economic minerals. Illustrating how these fairly straightforward methods can yield valuable results should highlight commonalities in **AT** localization and geophysical theory and hence optimize ***PGM*** development and successful **AT** discovering.

Let's assume that there is only one **AT** in the area. This area is divided into N equal cells. For simplicity each cell is assumed to have the same probability of containing the **AT**. Thus, the probability of finding the **AT** is equal to $P = 1/N$ in each cell. Hence, the entropy of experiment β (discovery of **AT**) is $\log_2 N$.

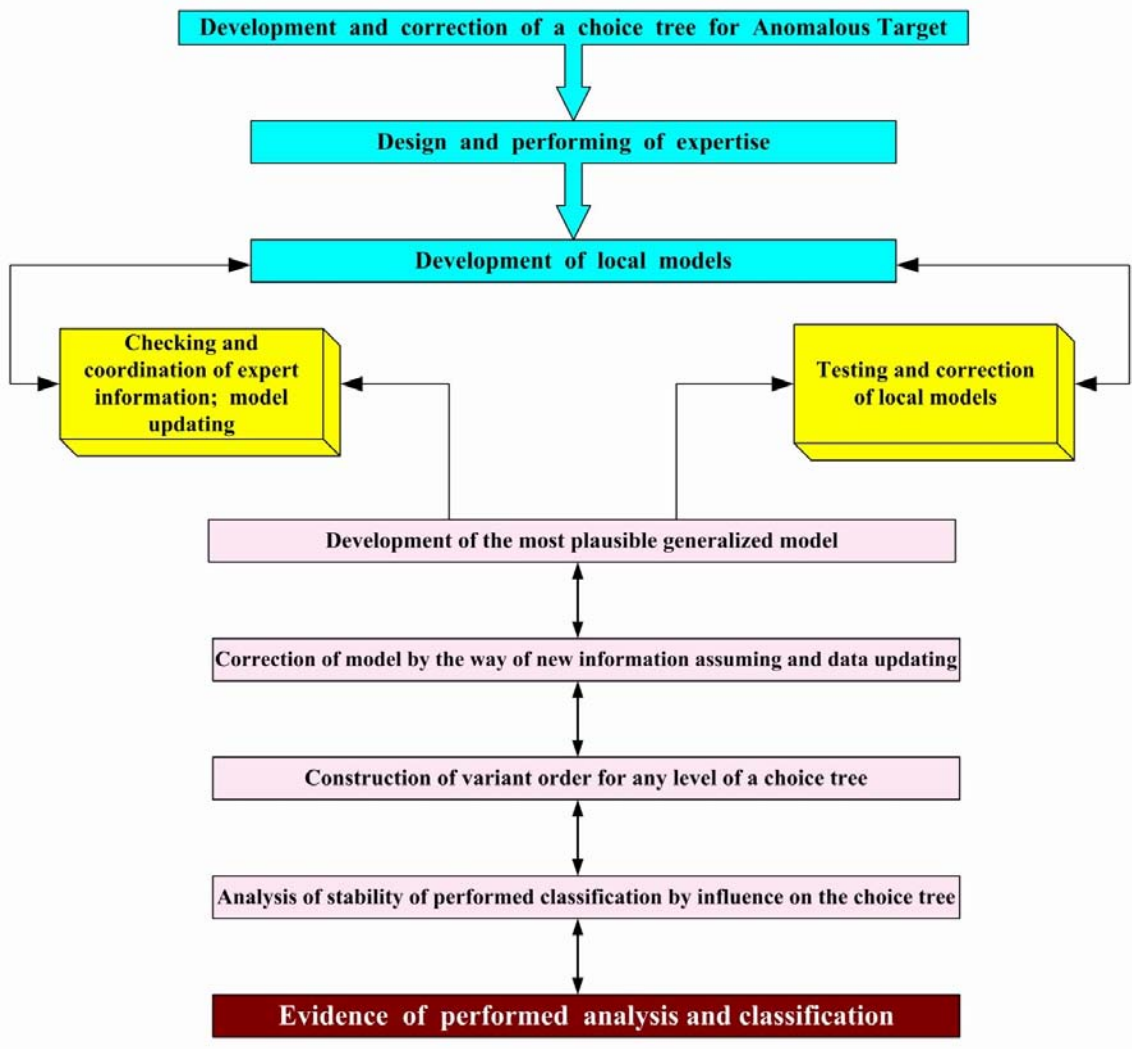


Figure 2. Flow-chart of integrated geological-geophysical analysis of combined data obtained in geological-geophysical prospecting by use of comprehensive informational approach

The entropy is determined using following expression:

$$H(\beta) = -\sum_{i=1}^{N} P(B_i) \cdot \log_2 P(B_i), \qquad (3)$$

where $P(B_i)$ is the probability of a B_i outcome (B is the range of outcomes of experiment β).

In this situation the $H(\beta)$ value $(\log_2 N)$ is maximum possible uncertainty. Experiment α (geophysical observation) gives additional information. The A value is a range of outcomes for experiment α.

The difference between uncertainties in the β results before and after experiment α serves to estimate the information in α as related to β:

$$I(\alpha, \beta) = H(\beta) - H(\beta|\alpha), \qquad (4)$$

where $H(\beta|\alpha)$ is the conditional entropy for experiment β (provided that experiment α has been conducted).

The conditional entropy is the average value of a random variable taking a $H(\beta_i|\alpha_i)$ value with a probability of $P(A_i)$:

$$H(\beta_i|\alpha_i) = \sum_{i=1}^{N} P(A_i) H(B_i|A_i). \qquad (5)$$

Estimating the efficiency of individual methods

When selecting methods for integration, it makes sense to evaluate the amount of information provided by each.

Starting from a well-investigated area (with an equal distance between observation points) typi-

cal of the region under study, it is assumed that 1/50 of it contains an **AT**. It is *a priori* assumed that the Bouguer gravity field over **AT** occurrence (anticline structure) is always positive, whereas in the empty part (not containing **AT**) of the area it may be either positive or negative with equal probability. In other words, it is known *a priori* that 2% and 98% of the area are **AT**-containing and empty, respectively, and in 49% and 51% of this area the Bouguer gravity anomalies, respectively, are negative and positive. The results of experiment β can be designated as follows: B – **AT** occupying part of the area, $\overline{B}$ – empty part of the area. Thus, $P(B)=0.02$, $P(\overline{B})=0.98$. According to expression (3) $H(\beta)\cong 0.14$.

The result of experiment α is expressed as follows: A is a positive field, $\overline{A}$ is a negative field. The relative partial entropy (after recording the positive Bouguer gravity at the measurement point) can be calculated in the following way: $P(A)=0.51$; $P(\overline{A})=0.49$; $P(B|A)=2/51$, $P(\overline{B}|A)=$ $=1-P(B|A)=49/51$. Thus, $H(\beta|\alpha)\cong 0.24$. According to the recorded negative Bouguer gravity, the area is certainly empty: $H(B|\overline{A})=0$. Consequently, the partial entropy for experiment β under the conditions of α, as stated in Eq. (5), is $H(\beta|\alpha)\cong 0.12$. Thus, the uncertainty of the **AT** determination decreased after Bouguer gravity observation/computation from 0.14 to 0.12.

By taking into account the cost of each measurement, the effectiveness of respective methods can be estimated (e.g., Eppelbaum et al., 2003). For this purpose it is sufficient to compare the values (costs) of the information units provided by each method. On this basis, a valid solution for a reasonable integration of the methods can be made.

Estimation of information by indicator (field) gradations

The applied geophysical fields usually have maximal and minimal intensity within studied areas. The difference between the maximal and minimal intensities may be subdivided into some intervals (gradations). Gradations of indicators can be also used to obtain information about the types of **AT**. Physical fields, geochemical analyses, **AT** features, etc. can serve as indicators. Let $P(A_i|B)$ denote the posterior probability of finding the i-th gradation of indicator A (e.g., magnetic field intensity) over the targets B, $P(A_i)$ is the prior probability of finding the same gradation in a survey area. Thus the partial information on the presence of target $I_{A_i\to B}$ contained in the recorded A_i gradation takes the following form:

$$I_{A_i\to B}=\log_2\left[\frac{P(A_i|B)}{P(A_i)}\right], \qquad (6a)$$

as the uncertainty in the recording of A_i before the survey was $\log_2 P(A_i)$ and after the survey – $\log_2 P(A_i|B)$.

Similarly,

$$I_{A_i\to\overline{B}}=\log_2\left[\frac{P(A_i|\overline{B})}{P(A_i)}\right]. \qquad (6b)$$

Statistically, the probabilities (or, to be more precise, relative frequencies) are expressed by the following ratios: S is the total number of values, S_i is the number of values occupied by the i-th interval of the A_i values, S_p is the total number of points reflecting the **AT** projections to earth's surface, and S_{pi} is the number of points common for interval A_i and the **AT** projections.

Then:

$$P(A_i)=\frac{S_i}{S},\quad P(A_i|B)=\frac{S_{pi}}{S_p},\quad P(A_i|\overline{B})=\frac{S_i-S_{pi}}{S-S_p}.$$

The increment in information contained about the presence of the object

$$\Delta I_i=I_{A_i\to B}-I_{A_i\to\overline{B}}=\log_2\left[\frac{P(A_i|B)}{P(A_i|\overline{B})}\right] \qquad (7)$$

are summed up in each elementary cell of the studied geological site.

To estimate the informational significance, the following expression can be used:

$$I_{A\to B}=\sum_i\left[P(A_i)\cdot I_{A_i\to B}\right]. \qquad (8)$$

The estimates served to substantiate the ratio between the informational significance, cost and time (see Eq. (1)). To normalize the results, the following semi-empirical expressions (obtained on the

basis of informational approach and long-term experience in the field of applied geophysics) can be used (on example of geophysical methods I and II):

$$\Omega_I = \frac{I'_{A\to B(I)}}{C_{(I)}/C_{(II)} \cdot T_{(I)}/T_{(II)}}, \quad (9a)$$

$$\Omega_{II} = \frac{I'_{A\to B(II)}}{C_{(II)}/C_{(I)} \cdot T_{(II)}/T_{(I)}}. \quad (9b)$$

Comparison the corresponding factors will enable to estimate the geophysical method effectiveness.

Estimates of the efficiency of geophysical integration based on the probability of type I and type II errors

Classification efficiency can be estimated quantitatively not only for separate methods, but also for geophysical integration by calculating the reliability of revealing **AT**. Let's assume that in some region 20 anomalies have been contoured and localized by a set of geophysical methods. The revealed anomalies were divided into 3 groups with various degree of desired **AT** discovering. Under the assumption that the results of drilling are absolutely reliable, classification reliability can be assessed by calculating the probability of type I and type II errors.

The probability of a type II error (M_2) is expressed as the relative frequency of an erroneous diagnosis for objects from sampling B (**AT**). The probability of a type I error (M_1) is expressed as the relative frequency of an erroneous diagnosis for objects from the sampling $\overline{B}$ (the remainder of the objects). These errors are used to determine the total unconditional error of separation q between the classes B and $\overline{B}$ (i.e. the risk of an erroneous solution):

$$q = M_2 P(B) + M_1 P(\overline{B}), \quad (10)$$

where $P(B)$ and $P(\overline{B})$ are the prior probabilities of the appearance of objects of the first and second classes, respectively.

If $P(B) = P(\overline{B}) = 0.5$, then q value corresponds to the intersection area of distribution densities $P(X|B)$ and $P(X|\overline{B})$. Here X is the separation index. It can represent geophysical field amplitude or gradient, the value of integrated indicator, etc.

The separation reliability (γ) is:

$$\gamma = 1 - q. \quad (11)$$

The total empirical error should be compared to the theoretical error. The approximation of the errors can confirm a correct assumption and provide high reliability of identification. Using logical-informational methods (Khesin et al., 1996), the classification reliability is estimated solely from empirical errors.

The errors due to assigning observation results to a class (with or without the **AT**) can be determined as follows. The absence of anomalies for the complex indicator in a known target- containing area is a type II error, or "omission of target". The presence of these anomalies in the empty part of this area is a type I error, or a "false alarm".

Comparing these rapid results with those of a more complex integration can also be used to estimate the respective errors and the reliability of classification. From the previous experience was recognized that the hydrocarbon nature of 14 out of 20 revealed gravity-magnetic anomalies in the Middle Kura Depression (Azerbaijan) was confirmed (Khesin et al., 1985). New **ATs** were not revealed at the areas where geophysical methods were applied. Thus, $M_1 = 0$, $M_2 = 14/20$. Assuming that $P(B) = P(\overline{B}) = 0.5$, and taking into account Eqs. (10) and (11), then $q = 0.70$ and $\gamma = 0.30$.

Calculation of information parameters

Typically, the first step in the qualitative interpretation involves visual inspection of profile observations or compiled maps. However, this simple analysis is often not sufficient to locate buried objects. Detecting any geophysical anomalies caused by **AT** is often difficult because the effect may be masked by influence of surrounding inhomogeneties of different sizes and intensity. Various transformation and filtering procedures have been developed for more effective localization of finite objects (Telford et al., 1990; Parasnis, 1997, etc.). We have shown elsewhere (Khesin and Eppelbaum, 1997; Eppelbaum, 2013) that applying information parameters often overcomes these problems. The method involves considering that the noise component – the combined effect of the surrounding inhomogeneties that are not associated with the target objects – is random. The amount of information (I_i) at each observation point by application of the i-th method is

$$I_i = -\log_2 P_j \quad (12a)$$

or

$$I_i \cong \log_2\left(\frac{H_i}{\Delta H_i}\right), \qquad (12b)$$

where P_j is the frequency rate of the j-th interval of the i-th indicator (field) in the histogram (more precisely, Bayes' evaluation of the probability that the results will end up in the j-th interval) and H_i and ΔH_i are the amplitude and determination error of this indicator, respectively.

Eppelbaum et al. (2008) proposed the following expression:

$$I_i = U_i\left(\sum_i^n U_i\right)^{-1} \log_{10}\left[U_i\left(\sum_i^n U_i\right)^{-1}\right]K, \qquad (12c)$$

where U_i is the geophysical observation at i-th point ($U_i > 0$) in the area under study, n is the total number of observations, and K is a some coefficient.

After summing the information elements that suggest *a priori* that a target object is present, the random noise and components caused by dissimilar geological features are suppressed. In order to avoid singling out fictitious objects by the plot of $\frac{1}{n}\sum_{i=1}^n I_i$, which can occur when a large amount of information is contained in the data of only one or two methods, an additional complex criterion that depends on the number of significant indicators can be calculated while adjusting for their relative influence:

$$I_{\text{integr}} = \sum_{k=1}^{\frac{n(n-1)}{2}} \frac{(I_p)_k}{(I_p)_{\max}}, \qquad (13)$$

where I_p is determined from the formula

$$I_p = (I_1 + I_2)\frac{I_1}{I_2}, \quad (I_1 \le I_2),$$

by using pairwise combinations of the n methods employed.

The results of the parameter calculation may be compiled as maps of I_i and I_{integr}. To avoid missing deeply embedded objects, in some cases it is better to use frequency rates of average values or average field estimates on a sliding scale instead of the P_j and H_i values, respectively. The correlation of I_{integr} with the sum of information elements makes it possible to avoid missing an object which for these or other reasons, was not revealed by other indicators. The combination of indices permits certain interpretative conclusions.

In practice J_i is usually replaced by the relative amount of information, also known as the coefficient of informativity (Khesin et al., 1996):

$$K_i = \frac{J_i}{\bar{J}_i}. \qquad (14)$$

The value of $\bar{J}_i$ determines the information obtained when the result of U_j falls into the x_j interval of the histogram with an equal probability of falling into any of the R intervals. According to probability principles (Ventsel, 1969; Daston, 1988), it is equal to the average (complete) information obtained when using a single method:

$$\bar{J}_i = \log_2 R. \qquad (15)$$

The application of K_i takes differences in the ranges of different fields into account. However, the application of expressions (11) and (13)–(15) may not be effective for sparse sampling.

Estimating integration efficiency by localization of weak anomalies

If a set of methods is focused on investigating independent indicators of equal value, the anomaly detection reliability γ can be described by an error function (probability integral) (Khesin and Eppelbaum, 1997) as:

$$\gamma = F\left(\frac{\sqrt{\sum_i \upsilon_i}}{2}\right), \qquad (16)$$

where υ is the ratio of the anomaly squared to the noise dispersion for each i-th geophysical field, and F is the probability integral of type

$$F(t) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{t} e^{\left(\frac{-x^2}{2}\right)}dx.$$

Now let us assume that the anomaly is indicated by three points and that the mean square of the anomaly for each field is equal to the noise dispersion. For a single method, the reliability of the detection of an anomaly of a known form and intensity by Kotelnikov's criterion (e.g., Borda, 2011) is expressed by $F(t)\left(\sqrt{\upsilon_i}/2\right)$. Hence the reliability

for individual methods is 0.61 and 0.77 and 0.87 for a set of two or three methods respectively. This means that the q value (risk of an erroneous solution) when integrating two or three methods decreases by factors of 1.7 and 3.0, respectively (according to Eq. (11)). A comparison of the risk with costs C yields an optimum set of methods.

APPLICATION OF THE INFORMATION METHODOLOGIES ON FIELD EXAMPLES

Let's begin to consider application of the informational parameter on the regional gravity field processing. It is well-known that the South Caspian Basin (*SCB*) is one of the main hydrocarbon provinces in the world (Alizadeh, 2005). The satellite gravity data of the *SCB* were obtained from the World Gravity DB as retracked from Geosat and ERS-1 altimetry (e.g., Sandwell and Smith, 2009). A highly positive factor is that these observations were made with regular global 1-minute grids and the error of gravity data computation for the newly arrived data is estimated at 1.0-1.5 mGals (Sandwell et al., 2013). The gravity data retracked to the Earth's surface are the close to free air gravity and can be effectively applied to the tectono-geophysical zonation (Eppelbaum and Katz, 2011). The compiled gravity map (Figure 3A) shows the gravity pattern within the *SCB* and south-west land bordering. The gravity data are ranging from -180 up to +420 mGals, and the anomalies in the center of the *SCB* are not brightly expressed. After application of the informational approach (Eq. (12c)), the image was significantly transformed (Figure 3B) and the gravity anomalies in the *SCB* can be effectively recognized (it should be noted that in the both maps the same color pattern was applied). Geological-geophysical examination of the transformed anomalies may be an interesting problem, but it is beyond the scope of this paper.

A Bulla-Deniz gas deposit located in the Bay of Baku (Azerbaijan) is one of rich deep hydrocarbon accumulations occurring below 5,000 m within the *SCB* (Guliyev et al., 2011). To calculate the parameter I_{integr} (see Eqs. (12a) and (13)) three different fields were employed: local magnetic anomalies ΔT (marine survey data), second horizontal derivative of the gravity potential W_{xz} (data from the bottom gravity survey were utilized), and $\Delta H/H$ (relative changes of the sea bottom topography) (Figure 4) (modified after Eppelbaum and Khesin, 2012). As can be seen from this figure, both faults, associated with the pay section, are reflected in the graph of I_{integr}. The large amplitude of the SW anomaly of the I_{integr} parameter compared to NE may be explained by the proximity of the SW fault to the surface of the sea bottom.

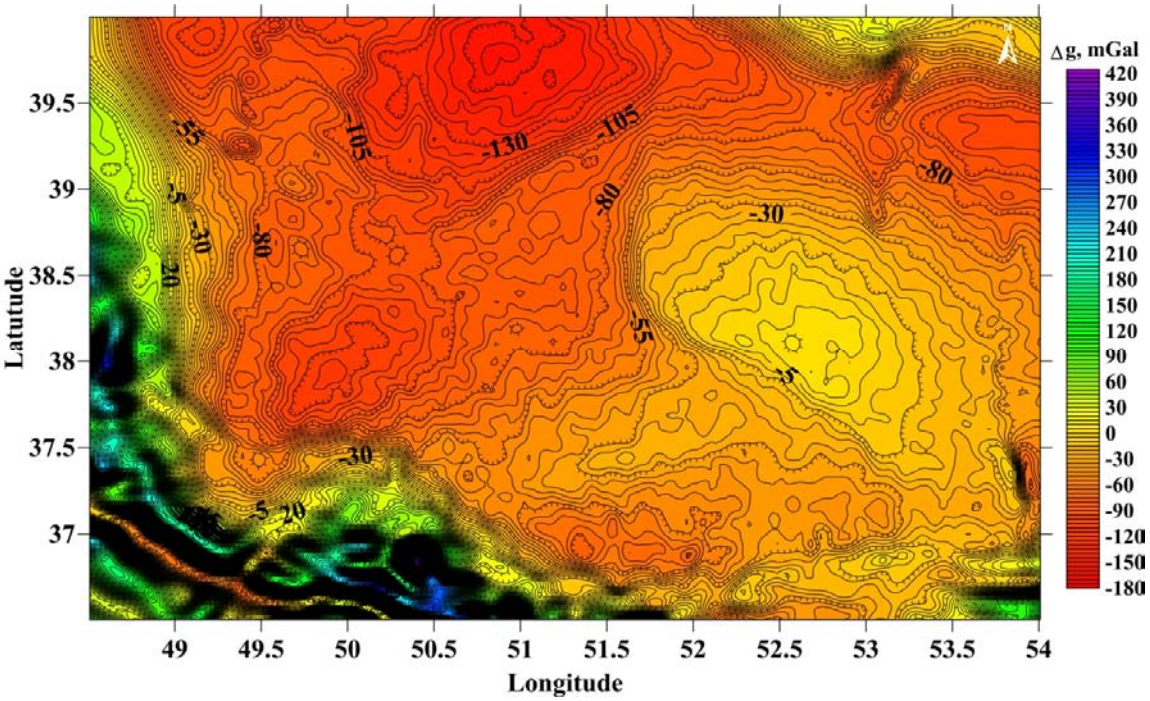


Figure 3A. Satellite gravity map of the South Caspian Basin and its SW border compiled on the basis of Geosat and ERS-1 altimetry data

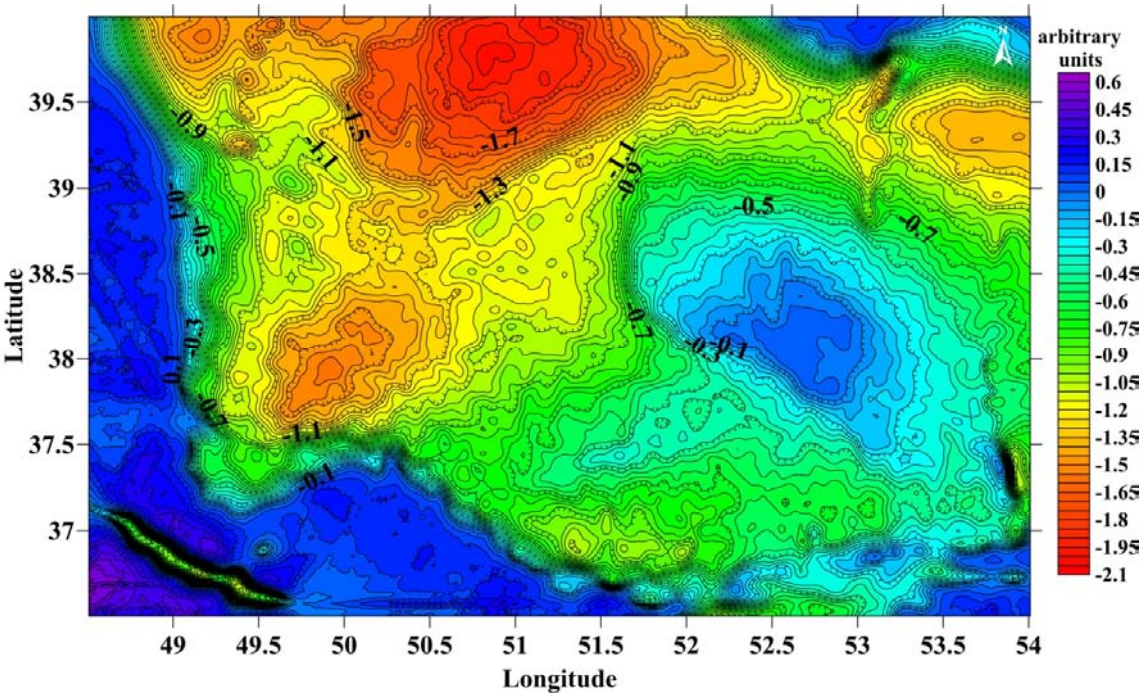


Figure 3B. Map of the informational parameter I_i transformed from the map presented in Fig. 3A

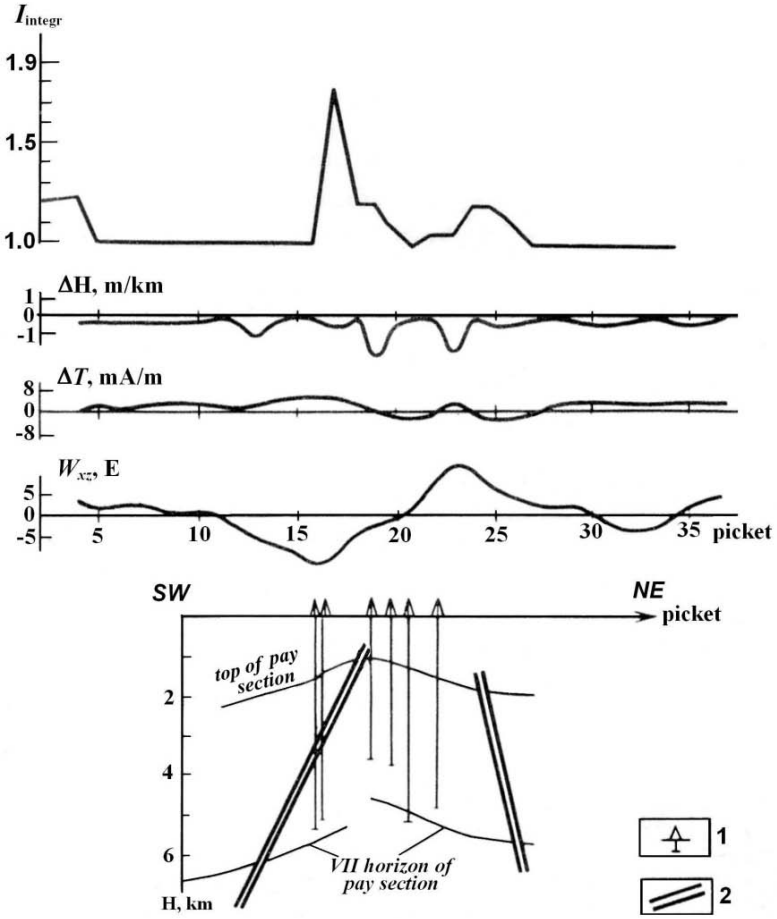


Figure 4. Qualitative delineation of faults by computing parameter I_{integr} at the area of Bulla (Baku Archipelago, Caspian Sea)
(1) deep wells, (2) faults delineated by combined analysis of geological and geophysical data

A gold-pyrite deposit Gyzyl-Bulakh is situated in the Mekmana ore district (Lesser Caucasus, western Azerbaijan) (Azizbekov et al., 1972). In this deposit gravity field (Δg_B), magnetic field (ΔT) and *VLF* (Very Low Frequency) electromagnetic field were employed (Figure 5). In gravity and *VLF* (vertical component H_z) fields small positive anomalies over the ore body were observed, whereas in magnetic field a negative anomaly was registered (the pyrite body with gold mineralization does not contain magnetic minerals and occurs in a magnetic medium). Integration of these geophysical methods (Eqs. (12b) and (13) were used) enabled to obtain a significant anomaly I_{integr} clearly indicating the position of the **AT** (ore body) upper edge.

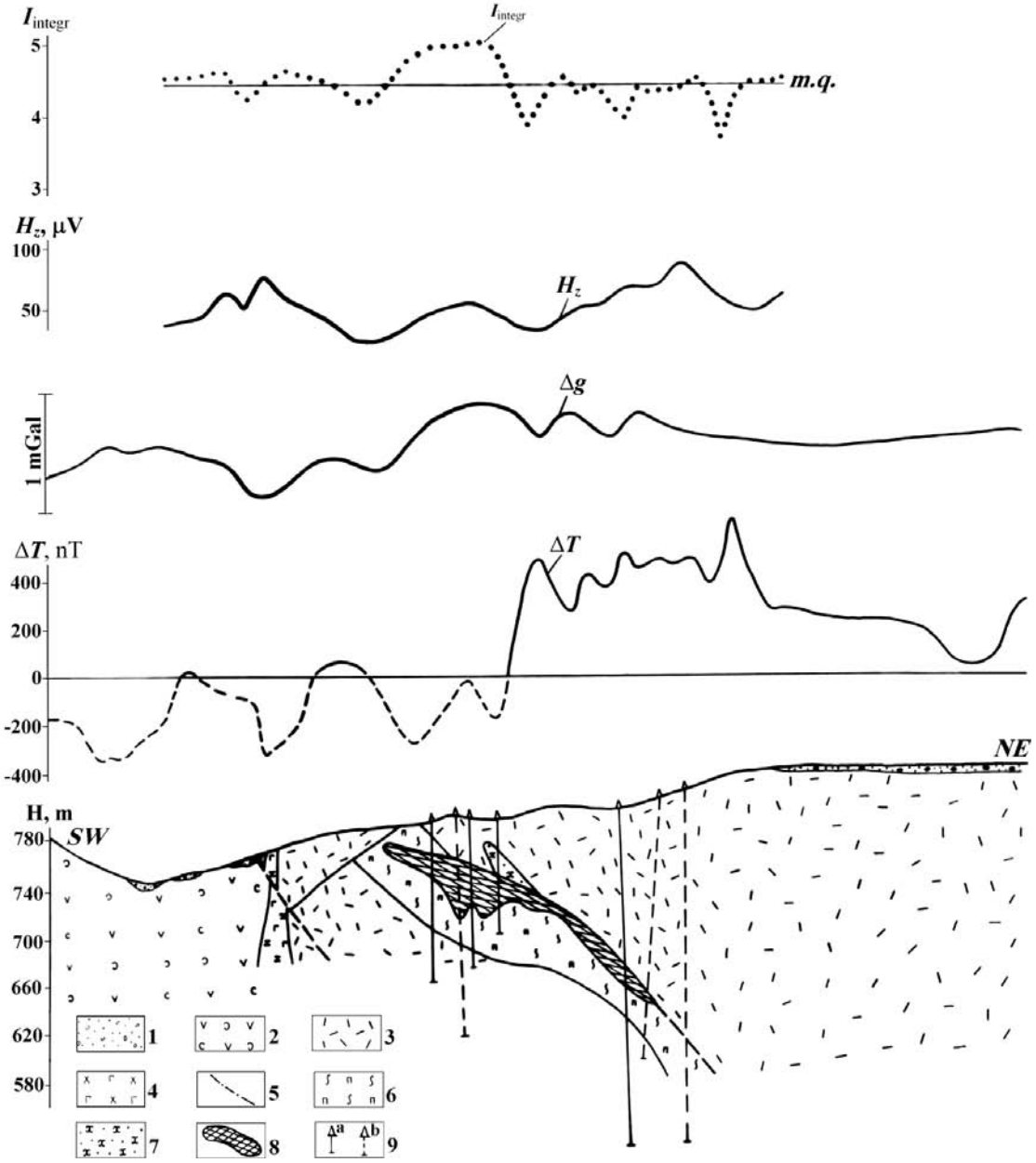


Figure 5. Singling out of the desired object (ore body) by summing up the amounts of information obtained by different geophysical methods in the Gyzyl-Bulag gold-pyrite deposit (Lesser Caucasus, western Azerbaijan) (on the basis of Eppelbaum (1989))
(1) Quaternary deluvial deposits; (2) tuffs and lavas of andesitic porphyrites, (3) tuffs of liparite-dacitic porphyrites; (4) dikes of andesite-basalts; (5) disjunctive dislocations; (6) zones of brecciation, crush and boudinage with lean pyrite-chalcopyrite ore; (7) zone of brecciation, crush and boudinage with rich impregnating mineralization; (8) massive pyrite-chalcopyrite ore; (9) drilled wells: (a) on the profile, (b) projected on the profile

Integration of gravity, VLF and temperature data in the mine of Katsdag polymetallic deposit (southern slope of the Greater Caucasus, north-west Azerbaijan) was shown in (Eppelbaum et al., 2014). However, the **ATs** in mines (it is a significant difference from land or satellite surveys) can occur not only below, but in all surrounding space that complicates employment of informational algorithms.

CONCLUSION

The information value of applying geophysical (geochemical, geological) methods for searching economic minerals can be estimated using various probabilistic-statistical procedures. The components of these procedures as it shown in this article can serve to assess the informativity of not only a single geophysical method but also of any geophysical integration. Elements of information theory can be easily applied to optimize the process of target recognition and help reveal anomalous effects from an **AT** against the significant noise background (low signal-to-noise ratio). The simple convolution of geophysical information, cost and time suggested here serves to compare the parameters as a whole. Employment the information methodology has shown in a few examples from economic deposits in Azerbaijan.

REFERENCES

ALIZADEH, Ak.A. (Ed.). 2005. Geology of Azerbaijan. Vol. V – Physics of the Earth. Nafta-Press. Baku (in Russian).

AZIZBEKOV, Sh.A., ALIZADEH, K.A., SHIKHALIBEYLI, E.Sh., GADJIEV, T.G. 1972. Geology of the USSR. Vol. XLVII: Azerbaijan. Nedra. Moscow (in Russian).

BORDA, M. 2011. Fundamentals in information theory and coding. Springer.

BRILLOUIN, L.N. 1962. Science and information theory. 2nd ed. Academic Press.

DASTON, L. 1988. Classical probability in the enlightenment. Princeton Univ. Press. Princeton.

DUDA, R.O., HART, P.E. 1973. Pattern classification and scene analysis. John Wiley & Sons.

EPPELBAUM, L.V. 1989. The development of methods for processing and interpretation of natural geophysical fields in prospecting for pyrite ores under mountainous conditions. PhD Thesis. YuzhVNIIGEOFIZIKA (Baku, Azerbaijan) – Institute of Geophysics (Georgian Acad. of Sciences). Tbilisi (in Russian).

EPPELBAUM, L.V. 2013. Geophysical observations at archaeological sites: Estimating informational content. *Archaeological Prospection*, 21, 2, 25-38.

EPPELBAUM, L.V., ALPEROVICH, L., ZHELUDEV, V., PECHERSKY, A. 2011. Application of informational and wavelet approaches for integrated processing of geophysical data in complex environments. *Proceed. of the 2011 SAGEEP Conf.*, Charleston, South Carolina, USA, 24, 24-60.

EPPELBAUM, L.V., EPPELBAUM, V.M., AND BEN-AVRAHAM, Z. 2003. Formalization and estimation of integrated geological investigations: Informational approach. *Geoinformatics*, 14, 3, 233-240.

EPPELBAUM, L.V., EZERSKY, M.G., AL-ZOUBI, A.S., GOLDSHMIDT, V.I., LEGCHENKO, A. 2008. Study of the factors affecting the karst volume assessment in the Dead Sea sinkhole problem using microgravity field analysis and 3D modeling. *Advances in GeoSciences*, 19, 97-115.

EPPELBAUM, L., KATZ, Y. 2011. Tectonic-geophysical mapping of Israel and eastern Mediterranean: Implication for hydrocarbon prospecting. *Positioning*, 2, 1, doi: 10.4236/pos.2011.21004, pp. 36-54.

EPPELBAUM, L.V., KHESIN, B.E. 2012. Geophysical Studies in the Caucasus. Springer.

EPPELBAUM, L.V., KUTASOV, I.M., PILCHIN, A.N. 2014. Applied Geothermics. Springer.

GULIYEV, I., ALIYEVA, E., HUSEYNOV, D., FEYZULLAYEV, A., MAMEDOV, P. 2011. Hydrocarbon potential of ultra deep deposits in the South Caspian Basin. Adapted from oral presentation at the *AAPG European Region Annual Conference*, Kiev, Ukraine, October 17-19, 2010. Search and Discovery Article #10312.

KHALFIN, L.A. 1958. Information theory of geophysical interpretation. *Doklady AN USSR*, 122, 6, 1007-1010.

KHESIN, B.E., ALEXEYEV, V.V., EPPELBAUM, L.V. et al. 1985. Combined analysis of potential geophysical fields in the Middle Kura Depression. *Research Report*, YuzhVNIIGEOFIZIKA (Baku, Azerbaijan).

KHESIN, B.E., ALEXEYEV, V.V., EPPELBAUM, L.V. 1996. Interpretation of geophysical fields in complicated environments. Bookseries: Modern approaches in geophysics, Kluwer Academic Publ.

KHESIN, B.E., EPPELBAUM, L.V. 1997. The number of geophysical methods required for target classification: quantitative estimation. *Geoinformatics*, 8, 1, 31-39.

NIKITIN, A.A. 1993. Statistical processing of geophysical data. Bookseries: *Advanced Geophysics. Russian Experience*, 2, Electromagnetic Research Centre, Moscow.

PARASNIS, D.S. 1997. Principles of applied geophysics. Chapman & Hall.

SANDWELL, D.T., GARCIA, E., SOOFI, K., WESSEL, P., SMITH, W.H.F. 2013. Towards 1 mGal global marine gravity from CryoSat-2, Envisat, and Jason-1. *The Leading Edge*, 32, 8, 892899. doi: 10.1190/tle32080892.1, 892-899.

SANDWELL, D.T., SMITH, W.H.F. 2009. Global marine gravity from retracked Geosat and ERS-1 altimetry: Ridge segmentation versus spreading rate. *Journal of Geophysical Research*, 114, B01411, doi: 10.1029/2008JB006008, 1-18.

SHANNON, C.E. 1948. A mathematical theory of communication. *Bell Sist. Techn.*, 27, 3-4, 379-432, 623-656.

SVETOV, B.S. 1992. Information theory basis of geophysics. Bookseries: *Advanced Geophysics. Russian Experience*, 1, Electromagnetic Research Centre, Moscow.

TELFORD, W.M., GELDART, L.P., SHERIFF, R.E. 1990. Applied Geophysics. 2nd Ed. Cambridge Univ. Press. Cambridge.

VENTSEL, E.S. 1969. The Probability Theory. Nauka Publ. Moscow (in Russian).

ZHDANOV, M.S. 2002. Geophysical inverse theory and regularization problems. Ser.: *Methods in Geochemistry and Geophysics*, 36, Elsevier, Amsterdam.

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