Paper

Model that Solve the Information Recovery Problems

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Abstract—The main part of the information ensuring in information and communication systems (ICS) is the provision for the development of methods for monitoring, optimization and forecasting facilities. Accordingly, an important issue of information security is a challenge to improve the monitoring systems accuracy. One way is to restore the information from the primary control sensors. Such sensors may be implemented in the form of technical devices, and as a hardware and software systems. This paper reviews and analyzes the information recovery models using data from monitoring systems that watch the state of information systems objects and highlights its advantages and disadvantages. The aim of proposed modeling is to improve the accuracy of monitoring systems.

Keywords—accuracy, information recovery, model, monitoring.

1. Introduction

Solving direct mathematical problems require accurate functions that will be able to describe physical phenomena, e.g., sound propagation, heat distribution, seismic vibrations, electromagnetic waves, etc. Medium properties in which the changes occur are described by equation coefficients. Equations coefficients are chosen to provide boundary conditions for the existence of phenomena in the environment. These values describe the initial state of the process, its properties, the boundary of data, reliability, etc. Such indicators are considered known. The therm called verge of reliability occurs when research area has limitations or during the stationary cases study, when the lack of dynamics does not allow to set the exact boundaries of the measured values deviation.

Indicated provision of the data unreliability can be distributed to informational medium. It may be also extended to those phenomena, which are investigated within them. Information environments have high physical and informational complexity, and their properties are often unknown. It means that there is need to formulate and solve the inverse problems to specify:

- the equations coefficients,
- unknown primary and/or boundary conditions,
- location, boundaries and other physical and information spaces that include under study processes.

These tasks are improper in most cases because they disrupt at least one of three common correctness properties. At the same time, the sought equation coefficients are usually density, electrical or thermal conductivity and other investigated medium important properties. When analyzing information medium, there an additional coefficients can be applied:

- data reliability as a property to preserve the semantic meaning,
- data reliability as a property to secure the electrical signals recovery, and so on.

The analysis of information and communication or software and hardware systems, e.g., the monitoring information space systems by search engines also requires the inverse problems solution. They arise while finding location of a given physical or logical object, its form, structure, or type of information impurities, defects in the information environment, sources defects, etc.

As can be seen in this software and hardware applications set, nowadays the theory of inverse and ill-posed problems is rapidly evolving science area.

Total requirements for software and hardware information and communication systems have become the basis for the systematic development of the converged architecture basic principles. This work is based on centralized services. Typically, services are combined into a single group (pool), which reduces the cost of their use. On this basis, cloud data processing technology has been developed and implemented. Data processing can be done by the user through existing network services, which are designed to serve a wide range of queries. They provide interaction between distributed software and hardware environment for cross-platform. In this case, any information about the user's location or his hardware and software configuration is unknown. Details are located in secure data centers. Data comes in data centers through special monitoring system and its reliability must be extremely high. Any distortion leads to the need for inverse problems solutions. Lack of data when modeling such systems also requires the inverse problems solution. Most of these are ill-posed. Their solutions have been developed over entire period of physical-information environments existence. The appearance of the fundamental works by A. M. Tikhonov allowed creating the modern theory of inverse problems solution. The concept of a regularizing algorithm was taken as a basis for the theory. The author observed the class of problems in which small changes in the initial data values lead to significant variations in the processing of measurements in physical environments. Later, the theory was extended to the problems of:

- unstable convolution type integral equations solution,
- incoming signal restoration by the outgoing signal values, considering the system impulse response.

Much later, the Tikhonov's theory for solving inverse problems allowed to get solutions for:

- processes of multi-DF (Direction Finding) signal on one frequency,
- radio emission sources identification, which was the beginning of the monitoring systems.

Nowadays monitoring systems are a broad class of devices. They have extensive physical and information functions and are based on ICS. The term "monitoring" implies that it is the observing and recording data process about phenomena or objects, or about changing their information status. The authors take into account that this process occurs at time intervals that are adjacent to one another. During these intervals the data value is not significantly changed. The most recent observation about the irrelevance of information changing and its consequences, is one of the major challenges in this article.

In general, the data recovery problem in ICS can be displayed by an operator equation of the form [1]–[6]:

$$Ay = f\,, \tag{1}$$

where A is the compact linear operator, y is the function, which aims to solve mathematical inverse problem of restore information about the objects status of information-control systems, and f stands for function, based on the results of the experiment.

According to [7] the inverse operator A^{-1} may not exist causing the problem incorrect [8], [9]. This shows that there is not only one or unstable solution. An example of this is degenerate or fuzzy defined System of Linear Algebraic Equations (SLAE) (1).

Difficulties in dealing with degenerate and fuzzy defined algebraic equations are well known in practical problems related to digital signal processing. This is explained by the fact that the digital processing calculations are performed with finite precision. Naturally, in this case no one can determine whether a given system of equations are degenerated or fuzzy defined. This implies that fuzzy defined and degenerated systems can be indistinguishable within the specified accuracy. Thus, the objectives formulation and purpose of the article is to analyze models of problem that solve information retrieval, information in which can be obtained by monitoring systems that watch the state of information systems objects in purpose to increase the data accuracy and an overview of their advantages and disadvantages.

Solutions of applied tasks in information retrieval monitoring systems are based on the Fredholm integral type I equation. It uses a variety of methods that providing for the regulating parameters imposition. These include methods mentioned in the researches and publications analysis given below. However, existing methods for finding the regularization parameter is not always ensure finding the optimal value at which the error of solution may be minimal. The article is devoted to the unsolved part of the overall problem. The essence of the article and it's scientific innovation are in the need to find a multi-criteria model for data recovery, providing a choice point solutions on the Pareto set. It is necessary to identify and take into account possible limitations on the permissible vector criterion range, if the Pareto set belongs to this area. Besides, it is necessary to find and show the selected model shortcomings.

2. Analysis of Approaches that Solve Ill-Posed Information Restoring Problems

Nowadays there is a wide range of different approaches to solve ill-posed problems. The basis for the research in this area is the A. M. Tikhonov's work, who created the mathematical theory of ill-posed problems. These include his method of regularization, Lavrentiev's method of replacing, Ivanov's method of selection and quasi-solution and others. Also, there were developed methods for iterative, statistical, local, descriptive regularization, suboptimal filtering, solutions on the compact and others. Foreign development methods are optimal filtration of the Kalman-Bucy and Wiener, method of controlled linear filtering (Beykusa-Gilbert), and others. Although these methods are in principle more precise, the methods proposed by mentioned scientists (primarily Tikhonov regularization method) require much less additional information about the solution and therefore are more widely used when solving ill-posed problems.

To study the behavior of complex physical objects or processes, the authors use a systematic approach, which is characterized by the determination of a set of properties and relationships inherent in the object or process. Researching properties often contradict each other, but neither one of them cannot be neglected, because only all together they give a complete object picture. For ill-posed problems, such contradictory properties or partial quality criteria in multiobjective formulation can be resulting solution stability and accuracy. Multicriteria problems are complex because their computational complexity depends linearly on the vector criterion dimension and exponentially on the desired solution dimension vector. In addition in many studies the effectiveness of multi-objective optimization is the assertion for a wide class of problems.

3. Analysis of Finding the Optimal Regularization Parameter Methods

In practical tasks the right side of the operator Eq. (1) and matrix elements (i.e., the coefficients of the system) are frequently given by their approximations $\left\|\tilde{f}-f\right\|_{L_2} \leq \delta$ and $\left\|\tilde{A}-A\right\| \leq \xi$ with the upper bound of the right part and the operator. In this case this type of equation is solved: $\tilde{A}\tilde{y} = \tilde{f}$, where $\tilde{y} \in L_2$ – approximate solution, $\tilde{f} \in L_2$ – approximate function that most closely matches the experimental results, L_2 – common designation of studied events multitude. But it should be noted that there are an infinite number of system with this type input data, i.e. (A, f). Within the accuracy that can be a priori given with unknown tolerances, errors may be unnoticeable. In this case an approximate system $\tilde{A}y = \tilde{f}$ can be solved.

This paper introduces the concept of normal solution for solving degenerate and ill-conditioned SLAE system (1), which is stable against input data small changes. Here the normal solution of SLAE on the vector y^1 is called solution y^0, for which $\left\|y^1 - y^0\right\| = \inf\limits_{y \in F_A} \left\|y - y^1\right\|$, where $\left\| y^0\right\| = \sqrt{\sum_j^n y_j^2}$. Thus, the problem of solving SLAE is reduced to minimize the functional $\left\| y^0 - y^1\right\|^2$ on the set of vectors that satisfy the inequality $\left\| Ay - \tilde{f}\right\| \leq \delta$, so according to [10], [11], there is need to find vector that minimizes the smoothing functional:

$$M^{\alpha}\left[y, \tilde{f}, \alpha\right] = \alpha \left\|y^0 - y^1\right\|^2 + \left\|Ay - \tilde{f}\right\|^2, \qquad (2)$$

where α is the regularization parameter.

According to the foregoing, it is necessary to stave the parametric optimization problem, which is connected with great challenges (e.g. [1]–[6], [8]–[11]). It is also called the position of finding the optimal regularization parameter question. This follows from the fact that by definition of the general case, it should be searched with infinite precision in the interval $0 \leq \alpha \leq 1$.

When Eq. (1) is a linear integral operator with constant limits of integration, the signal reconstructing problem can be represented by "truncated" Fredholm's linear integral equations of the first kind, which is:

$$\int\limits_a^b Q(x,s) \cdot y(s) ds = f(x), x \in [c,d], \quad s \in (a,b). \qquad (3)$$

To solve the signal restoration problem for the Eq. (3) means finding the kind of signal $y(s)$, distorted by monitoring instrumentation with hardware function $Q(x,s)$ to a signal $f(x)$. Existing methods for solving the problem of information recovery typically use regularization, and they are extremely sensitive to errors in the results obtained in the monitoring process. In addition, they are not universal due to the fact that they shows acceptable results only for recovery tasks defined types, such as those that have precise initial conditions and well-conditioned system of equations, which can be reduced to Eq. (3).

4. Providing the Optimal Regularization Parameter Conditions

Methods mentioned in Section 3 for finding the regularization parameter are not always provide the optimal regularization parameter in which solution error given by Eq. (3) can be minimalized, i.e.:

$$\delta_y = \frac{\|y_\alpha - \bar{y}\|_{L_2}}{\|\bar{y}\|_{L_2}} \to \min, \qquad (4)$$

where y_α and $\bar{y}$ are obtained and exact solutions of the Eq. (3).

In this paper the concept of partial quality criteria is used, that are typical for multiobjective optimization, to identify the conditions for the solution to find. The quality of the Eq. (3) solution is estimated by set of frequency criteria:

$$I_j = \Phi_j\left[x, a, b, c, d, y\right], \qquad (5)$$

where $j = 1, 2, 3, \ldots, P$, functions Φ_j have continuous partial derivatives on y, and partial criteria given by Eq. (5) are the components of P-dimensional vector criterion $I = (I_1, I_2, \ldots, I_P)$.

Suppose vector's I criterion is limited by permissible area $I \in \Omega(I)$. Each component of the vector's criterion I is described by Eq. (5), which is specified on solutions $Y \in Y$ of integral Eq. (3). Solution's multicriteria problem *IP* is to determine the extremes $\{y^*(s)\}, y^* \in Y, I^* \in (I)$ (that under the given circumstances conditioned by the degree of a priori information about the solution $y(s)$, which optimize the vector's criterion I.

Let's take Y as the given set of possible solutions, composed of vectors $y = \{y_i\}_{i-1}^n$ n – dimensional Euclidean space. The solution quality can be evaluated by set of conflicting partial criteria, which forms P – dimensional vector $Y(y) = \left\{I_j(y)\right\}_{j-1}^P \subset F$ specified on the set Y, which belongs to the class F admissible vectors effectiveness and which is limited by acceptable area $I \in \Omega$. Therefore, there is need to define a solution $y^* \in Y$, that under given conditions and constraints optimizes the solution $y(s)$ of Eq. (3). So the components of the vector $y(s)$ should be subjected to normalization, since the solution is defined on the set of efficient points (Pareto's area) only if all partial criteria reduced to a single dimension or dimensionless form. In [7] an objective normalization method which does not disrupt any of the equality of partial criteria and which does not depend on the scale was presented. In this case the components of normalization vector y_0 as partial criteria extremes are taken, which defined on the space of solutions:

$$y_0 = \left\{\sup_{s \in S} y_j(s)\right\}_{j=1}^P. \qquad (6)$$

Let's perform the efficiency vector $I(y)$ normalization by constrained vector I_{jm} and obtain the vector of relative partial criteria, i.e. normalized efficiency vector:

$$I_0(y) = \left\{I_j(y)/I_{jm}\right\}_{j=1}^P = \left\{i_0(y)\right\}_{j=1}^P. \qquad (7)$$

Assume that all partial criteria $I_j(y)$ require minimization and they all are non negative and constrained:

$$\Omega = \left\{ I \left| 0 \le i_j(y) \le I_{jm}, j \in [1,P] \right. \right\} . \quad (8)$$

According to the literature analysis, case given by Eq. (8) is the most common. The system of inequalities (8) is a structured demonstration of acceptable area $y \in \Omega$. In this area efficiency vector (6) has the form of given constrained vector:

$$y_0 = \left\{ I_{jm} \right\}_{j=1}^{P} , \quad (9)$$

as the supremum of partial criteria are specified constraints I_{jm}.

5. Restrictions on Finding the Optimal Solution

Depending on the presence and prior information type, approaches to solving multicriteria problems may be different. In the absence of such information just find any vector solution y^*, that provides only the condition (8) to limit [14], [15]:

$$I^* \in \Omega = \left\{ I | 0 \le I_j(y^*) \le I_{jm}, j \in [1,r] \right\}, y^* \in Y = Y^k \cup Y^C, \quad (10)$$

where $y^* \in Y = Y^k \cup Y^C$ is solution belongs to two areas: compromises Y^k (the Pareto's area) and agreement Y^C [16], [17]. With this method the optimal solution it often approximated. The main criteria method is often recommended for practical use. It assumes that for the optimization from a set I_j, where $j \in [1,P]$, only one of the possible criteria (e.g. first) is chosen as a criterion, and others are transferred to the constraints category. Thus output multicriterion problem artificially replaced by a single-criterion with constraints is:

$$y^* = \arg\min_{y \in Y} I_1(y), 0 \le i_j(y) \le A_j, j \in [1,P] . \quad (11)$$

Although this method can be justified only for the complex systems optimization, i.e., when to perform even the simplest coordination of contradictory criteria is not easy, one still could argue that ill-posed problems are also a complex systems [18]–[20], and the replacement of multicriterion optimization by single-criterion will be expedient.

6. Modeling Multicriteria Problems in Data Restoring Technology

In [21], [22] some of multicriteria models are reviewed. According to the first model, resulted in the sources, multicriterion problem defined by Eqs. (3)–(7) is reduced to minimize the linear form component scalar criterion with constant weighting coefficients:

$$I_{M_1} = \sum_{j=1}^{P} \alpha_j I_j, \alpha_j > 0, \sum_{j=1}^{P} \alpha_j = 1 . \quad (12)$$

In this case there is the problem of choosing weighting coefficients $\alpha_j, j = \overline{1,P}$. The scheme (12) in [12], [13] and [21], [22] is called the *integration optimality* model.

The second model in [21], [22] is defined as the *ideal (optimal) point in the space of quality criteria*. In each partial criterion (5) is optimized separately from others in the system of constraints (7). The result can be obtained by P optimal solutions, which are characterized by vectors $Y^{(j)}$, where $j = \overline{1,P}$. These solutions corresponds to the definition of partial criteria (7) $I_j^0(Y^{(j)}$, where $j = \overline{1,P}$, which are the coordinates of the ideal (optimal) point. Later the problem of minimizing the generalized norm puts up in the system of constraints (7):

$$I \left(\sum_{j=1}^{P} \left[I_j(y) - I_j^0 \left(y^{(j)} \right) \right]^L \right)^{\frac{1}{L}}, \; L \ge 1 , \quad (13)$$

The expression (13) with $L = 1$ represents a linear combination of vector components $I(y)$ and $I^0(0)$. For $L = 2$ the expression (13) coincides with the Euclidean norm $\left\| I(y) - I^0(y) \right\|$, and if $L \to \infty$ it is reduced to the form: $\max_j \left\{ I_j(y) - I_j^0 \left(y^{(j)} \right) | j = \overline{1,P} \right\}$.

In some cases, the multicriterion model (13), treats the function (7) minimizing problem by the relative deviations sum of squares from their optimal values:

$$I_{M_2} = \sum_{j=1}^{P} \left[\frac{I_j(y) - I_j^0 \left(y^{(j)} \right)}{I_j^0 \left(y^{(j)} \right)} \right]^2 . \quad (14)$$

For such cases multicriteria problem given by Eqs. (3)–(7) is reduced to minimize the function (14), and solution vector is chosen from the condition of minimization of the distance from the point corresponding to the space criteria selected solution vector to the ideal (optimal) point.

Modeling the multicriterion task by Eqs. (3)–(7) and Eq. (14) does not require weighting coefficients preselection α_j in the Eq. (12), but has a high computational complexity. This is due to solving P optimization problems in (3)–(7) for each partial criterion I_j to identify the ideal point coordinates $\left\{ I_1^0(y^1), I_2^0(y^2), \ldots, I_P^0(y^P) \right\}$ and solving the problem of minimizing additional functions in (7) to determine the optimal solution vector.

Next multicriteria model based on the scalar contraction of partial criteria for nonlinear compromise scheme [23], [24] is presented. It was was introduced in the theory of information recovery in [12], [13] does not require selection of weighting coefficients in the expression (12) and does not need a solution $P+1$ of optimization tasks, which is necessary for implementation in the others. Multicriterion problem given by (3)–(8) is reduced to the solution of a single optimization problem in expression [12]–[15] under the conditions (8):

$$I_{M_3} = \sum_{j=1}^{r} \frac{1}{1 - \frac{I_j}{I}} . \quad (15)$$

To set a certain criteria priority and achieve different sensitivity to variation problem parameters, instead of a unit

in the expression (15) numerator the weight coefficients α_j must be entered which imposed constraints $\sum a_j = 1$.
Necessary conditions for a minimum I_{M_3} give a finite system of equations:

$$\frac{\partial I_{M_3}}{\partial y_i} = 0, i = \overline{1,n}. \qquad (16)$$

After differentiation of Eq. (16), a low dimensioned system of nonlinear equations (SNE) is obtained, which leads to for example using Newton's method for SLE.
When the function $y_0(x), j = \overline{1,m}$ – continuous and strictly convex parallelepiped $\Pi_x = \left\{x \in E^n \left| a_i \leq x_i \leq b_i, i = \overline{1,n} \right.\right\}$, a scalar convolution by nonlinear scheme of compromise $\Phi(x) = \sum_{j=1}^{m} \alpha_j \left(1 - y_{0j}(x)\right)^{-1}$, $x \in \Gamma_x$, when normalization of partial criteria using expressions $y_{0j} = \frac{y_j(x)}{A_j}$, $A_j = \sup_{x \in \Gamma_x} u_j(x) j = \overline{1,m}$, has a single minimum on parallelepiped Π_x, which means being unimodal. Therefore, for the partial criteria it should be selected strictly convex function in order to problem of optimizing by the scheme (15) has a unique solution.
Multicriterial model given by Eq. (15) is sensitive to parameters changes defined by Eqs. (3)–(8). If there's one partial criteria I_j close to the upper limit I_{jm} allowable values (8) multicriteria model (15) implements the Chebyshev's action (minimax) operator in this partial criterion. In other cases multicriteria model (15) is equivalent to the integrated optimality operator with varying degree of equalization of partial criteria. The deterioration one of the partial's criteria is offsets by another partial improvement.

7. Conclusions

The presented analysis shows that multicriteria model provides selection of a point on Pareto's set. Thus if Pareto set belongs to this area it is necessary to take into account specified constraints on the range of allowable vector criterion. Accordingly, for solving multicriteria problems, which set constraints (8) on the components of the vector criterion, model (15) is recommended.
However, the drawbacks of the model should be taken into account:

- cumbersome of equations when a large dimension,
- CHP (16) can have many roots,
- if the solution lies on the constraints border, it will be found with an error, although less than required (i.e., it means that there is essentially exact solution).

As presented, the SLAR solution is unstable. The instability is the result of the presence of a large numbers, its representation and tolerances. Thus, the goal of future researches is to show that:

- if the solutions of these equations does not exist, then is there any point in using the Gauss method of least squares, which can lead to a pseudo-solution,
- if there is no unique solution, whether it may be possible to use the Moore-Penrose matrix pseudo-inverse, where the normal solution can be obtained,
- if the solution is unstable, whether it may be appropriate to use regular or sustainable methods, i.e. regularization or filtering.

The experts of data recovery in inverse and ill-posed problems are involved in the study of the properties and non-stable problems regularization methods. These tasks are distributed into a large set of physical and information processes. For IT processes and for information space monitoring systems, these problems are only in their developmental stage. Nowadays scientists are trying to create new methods to solve non-stable problems. While doing so, they suggest that the methods are suitable for use in informatization systems. In terms of linear algebra, this is equivalent to find approximate methods to search the normal pseudo-solution in algebraic linear equations systems. It is assumed that the methods can be applied to calculations in rectangular, degenerate or poorly conditioned matrices. It is the aim of the further researches on the issue which was discussed in this paper.

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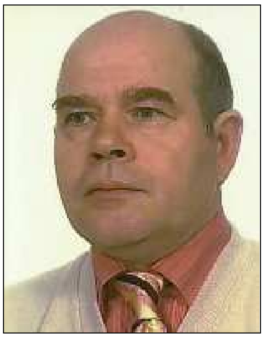

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