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INFORMATION TECHNOLOGY FOR AUTOMATED ASSESSMENT OF THE ARTILLERY BARRELS WEAR BASED ON SVM CLASSIFIER

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ABSTRACT

An information technology for the automated assessment of the has been developed wear level has been developed. Information technology is based on the analysis of acoustic fields accompanying a shot. The acoustic field of the shot consists of a ballistic wave accompanying a projectile flying out at a supersonic speed, and a muzzle wave generated when propellant gases are ejected from the barrel. The parameters of the ballistic and muzzle waves depend significantly on the level of barrel wear. This makes it possible to construct an automatic classifier of the barrel wear level based on the analysis of informative features of acoustic signals recorded by microphones near the weapon's firing position. The information technology is based on a binary SVM classifier. A set of records of acoustic fields of shots was synthesized on the basis of real signals recorded when firing a 155 mm howitzer. From the set of records, a training and test set of information features were formed for training the classifier and assessing its quality. Methods of preliminary data normalization of training and test samples are investigated. A technique for optimizing the classifier hyperparameters with instance cross-validation has been developed. The technique is a two-stage method for finding the optimal values of hyperparameters. In the first stage, the search is performed on an exponential decimal grid. At the second stage, the optimal values of hyperparameters are refined on a linear grid. A method for the binary classification of artillery barrels according to the wear level has been formulated. Checking the classifier on a consistent test sample showed that it provides the correct classification of barrel wear with a probability of 0.94. An information technology has been developed for classifying artillery barrels by wear level based on the analysis of acoustic fields of shots. Information technology consists of three stages: data preparation, construction, training an optimization of the binary SVM classifier and the operation of the binary SVM classifier. A field experiment was carried out, which confirmed the correctness of the basic scientific and technical solutions. An automated system has been developed for classifying wellbores by wear level.

Keywords: artillery barrel; wear level; ballistic wave; muzzle wave; binary SVM classifier; information technology

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1. INTRODUCTION

Barrel artillery was and continues to be one of the main components of the armed forces of the state, ensuring its security and sovereignty. Modern barrel artillery systems are complex technical systems capable of performing combat missions similar to those of missile systems, but with fewer resources and in a shorter time [1–2]. Analysis of military conflicts in recent decades shows the ever-increasing role of artillery units. The world experience of local wars and armed conflicts of the last decade of the XX century and two decades of the XXI century, and in particular, the experience of combat activity within the anti-terrorist operation zone in the east of Ukraine, suggests that up to 80 % of the volume of tasks to fire damage the enemy was assigned to field artillery [1]. One of the main points in the technical support of artillery units is the diagnostics of their materiel. The required effectiveness of the combat employment of artillery can only be achieved with proper diagnostics of the materiel of the artillery systems [3–4]. Modern information technologies and computing capabilities can provide a designated person making a decision about the state and life of a gun barrel with detailed measuring and diagnostic information [5]. The barrel is one of the main units in present-day artillery systems. It is a part of an artillery gun designed to direct a shell during shooting and impart the required velocity to it [6]. While firing, the barrel is subjected to enormous dynamic loads and therefore wears out. The state of the barrel largely determines the combat qualities of the weapon as a whole.

The barrel wear refers to all irreversible changes in the surface of the gun bore caused by the impact of shots on it and entails a decrease in the fighting

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qualities and effectiveness of the use of the gun [7]. Ultimately, wear can be considered as an integral process leading to the final result – a decrease in the initial velocity of the shell and an increase in its dispersion from shot to shot as a random variable [8]. Timely assessment of the level of barrel wear is not only a military-applied, but also a serious economic problem, since the cost of a modern gun barrel is up to 20–30 % of the cost of the entire artillery piece, and barrel failure is accompanied by serious economic losses. Therefore, the development of new technologies for assessing barrel wear is an urgent scientific and practical task.

2. THE REVIEW OF THE ISSUE

Known methods for assessing barrel wear can be divided into two classes: classical methods and methods using modern technologies. The simplest, but still most popular in troops, is the method of firing at vertically mounted shields at a distance of 40-60 m, in which oval holes appear [6]. If the ovality of holes as the ratio of the long axis length to the short axis length of at least one hole exceeds 1.5, the barrel is rejected. The method is empirical, theoretically insufficiently substantiated, and the obtained estimates of wear are very approximate.

Another group of classical methods are instrumental methods associated with a physical examination of the inner surface of the barrel in order to assess wear [9–10]. The oldest method of bore surface examination is a mechanical inspection. When examining barrels in such way, control discs or other calibrated templates are inserted into the bore from its breech end. When using mechanical measuring instruments for assessing wear, the subjective aspect is of great importance – the qualifications of the operator. In addition, such methods of instrumental wear control are characterized by high labour intensity and insufficient accuracy [11]. Calculation methods for assessing wear are based on calculating the residual life of the barrel according to statistical models and the history of the weapon's combat use (the number of shots, the charges and ammunition used) [12–13]. Calculation methods are rather laborious [13], however, the reliability of the results in relation to a specific cannon has not been confirmed [10].

More modern technologies for assessing barrel wear, which are actually information technologies, are based on assessing the state of the barrel by accurately measuring muzzle shell velocity by means of specialized radar devices – ballistic radar stations (BRS) or artillery ballistic stations (ABS) or muzzle velocity radars (MVR) [14–15]. BRS are centimeter-band Doppler radars [15]. These technologies provide the high accuracy of operational measurement of the initial velocity, but they have a number of disadvantages, the main one of which is the high cost of the set of equipment [16-17]. Their high expense is the main obstacle to the massive introduction of the radar in the field troops. On the other hand endoscopes are modern technology for assessing the level of barrel wear. Endoscopes make it possible to study in sufficient detail the state of the bore, present its image in any projection [18] and quantitatively process measurements [19]. Endoscopic technologies for the control of barrels have been raised to a robotic level [20]. These technologies allow obtaining complete and accurate information about the degree of wear of the bore, but their disadvantages are also the high cost of equipment and high labor intensity.

Analysis of literature data [1–20] makes it possible to establish the following. The existing technologies for assessing the degree of wear of artillery barrels are diverse, however, those that are available for widespread use in filed troops can be considered ideologically outdated, with low accuracy of assessment and practically unsuitability for automation. On the other hand, technologies based on modern methods of processing measurement information require expensive equipment, which is an obstacle to their practical implementation in military units. In [21–23], the characteristics of acoustic signals arising during the firing were analyzed. So, in [21], the characteristics of a ballistic wave from an artillery shot are investigated, article [22] is devoted to recognizing the caliber of a howitzer by acoustic signals of a shot, and in [22–23], the results of assessing the location of an artillery firing position by an acoustic method are given. Although works [21–23] do not directly address the issue of assessing barrel wear, they served as a prerequisite for research in this direction. In [24–25], a simple, low-cost and effective principle of assessing the state of artillery barrels from the acoustic field created by a shot is proposed. The acoustic field of the shot consists of a ballistic wave and a muzzle wave, the formation process of which is shown in *Fig. 1*. Ballistic wave is a shock wave (SW) created by a shell flying out of the barrel at supersonic speed, the center of which moves with the shell. SW can be registered inside the Mach cone [25]. A muzzle wave (MW) is created in the process of expansion of high-pressure gases when a shell leaves the barrel. The acoustic signal of muzzle wave propagates at the speed of sound from the muzzle of the gun barrel into the environment. It is shown that the parameters of BW and MW significantly depend on the level of barrel wear. This makes it possible to create an automatic classifier of the state of the barrels according to the parameters of the acoustic signals recorded when firing from the cannon.

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Fig. 1. **The process of sound production when firing a 152 mm cannon 2A36 "Hyacinth-B" (author's video filming):**
1 – shell; 1a – Mach cone, accompanying the shell; 2 – frontal emissions of powder gases; 3 – lateral emissions of powder gases through the compensator holes (muzzle brake) of cannon

However, in [24–25], the principle of diagnostics of the barrel is presented at a general level and has not been sufficiently studied in practical terms. A detailed study of it became the content of this article.

3. THE PURPOSE AND OBJECTIVES OF THE STUDY

The purpose of the study is to develop information technology for the automated classification of barrels by wear level based on acoustic signals of shock and muzzle waves accompanying an artillery shot.

To achieve the goal, the following tasks were solved:

– development of a method for binary classification of artillery barrels by their wear level;

– construction of information technology for classification of barrels;

– development of a scheme for an automated system for technical diagnostics of the state of the barrels according to a selected set of informative signs.

4. MAIN PART

4.1. Computer experiment

A large-scale computer experiment was prepared to test the possibility of automated classification of barrels. When solving the problem of automatic diagnostics of objects, in the general case, it is difficult to form a balanced sample of characteristics of serviceable and unserviceable objects (faulty objects are much less common than intact ones). Therefore, to study the issue of automatic classification of artillery barrels by the method of a computer experiment, a simulation set of records of acoustic fields from shots was generated. The basis for the imitation set was chosen from full-scale recordings of acoustic signals recorded during the firing of the M109A3GN howitzer [26]. From real digitized recordings of signals, a set of 300 classified recordings was formed, simulating acoustic signals from artillery shots in real conditions. At the same time, acoustic signals were artificially synthesized, simulating shots from barrels with wear.

Additionally, the concept of the barrel wear coefficient was introduced:

$$\eta = V^* / V,\ 0 < \eta < 1, \qquad (1)$$

where: V^* is the initial velocity of the shell fired from the barrel with wear; V – is the conventional tabular value of initial velocity of the shell for a given type of cannon, barrel, shell and charge.

The threshold minimum value η when synthesizing records was taken equal to 0.9 and for each record, it was chosen at random. To synthesize a specific record simulating a barrel with wear, the value of the barrel wear factor was taken equal to η_i =*rand* [0,9; 0,95], where $i \in [1, N]$, N is the total number of records in the simulation set. In addition, during the formation of a set of imitation records, were modeled such phenomena as wind noise on the recording microphones (in the form of a model of additive pink noise) and the reverberation of acoustic pulse signals in the surface layer of the atmosphere. The method for synthesizing a set of records is described in detail in [24]. Each record contained areas containing SW and MW signals using the Price-Urkowitz's energy detector [27]. Further, informative signs (IS) were identified that characterize SW and MW for barrels without wear and barrels with a certain level of wear.

IS were allocated for SW (*SW* index) and MW (*MW* index) in three domains: in the time domain (*time* index), in the frequency domain (*freq* index) and in the domain of cumulate parameters (higher-order spectral moments characterizing the fine structure of impulse signals) (*freq_cum* index) [28-29]. Thus, for each record, 6 subsets of informative signs (IS) $\left\{IS_{SW,i}^{time}\right\}$ $\left\{IS_{SW,i}^{freq}\right\}$, $\left\{IS_{SW,i}^{freq\_cum}\right\}$ $\left\{IS_{MW,i}^{time}\right\}$, $\left\{IS_{MW,i}^{freq}\right\}$, $\left\{IS_{MW,i}^{freq\_cum}\right\}$, $i = \overline{1, N}$ with cardinalities:

$\operatorname{card}\left\{IS_{SW,i}^{time}\right\} =$, $\operatorname{card}\left\{IS_{SW,i}^{freq}\right\} = 2$,

$\operatorname{card}\left\{IS_{SW,i}^{freq\_cum}\right\} = 2$, $\operatorname{card}\left\{IS_{MW,i}^{time}\right\} = 4$,

$\text{card}\left\{IS_{MW,i}^{freq}\right\} = 2$, $\text{card}\left\{IS_{MW,i}^{freq\_cum}\right\} = 2$, respectively, were obtained. The complete set of informative signs (IS):

$$\left\{IS_i\right\} = \left\{IS_{SW,i}^{time}\right\} \cup \left\{IS_{SW,i}^{freq}\right\} \cup \left\{IS_{SW,i}^{freq\_cum}\right\} \cup$$
$$\cup \left\{IS_{MW,i}^{time}\right\} \cup \left\{IS_{MW,i}^{freq}\right\} \cup \left\{IS_{MW,i}^{freq\_cum}\right\},$$

$\text{card}\left\{IS_i\right\} = 15$. The generated sets of informative signs made it possible to conduct a computational experiment to confirm the possibility of classifying barrels by wear level and to evaluate the classification quality indicators.

In what follows, since the classification results are binary, as the only indicator of the classification quality was chosen the assessment of the probability of correct classification, which was estimated as

$$\hat{p}_{corr} = N*/N_{TS}, \quad (2)$$

where: $N*$ – is the number of objects correctly assigned to the corresponding class;
N_{TS} – the total number of the test sample.

4.2. Development of a method for binary classification of artillery barrels by the wear level

4.2.1. General formulation of the problem of binary classification using an SVM classifier

The main task of the binary classification as applied to the diagnosis of artillery barrels by the level of wear is to determine, by a set of informative signs of acoustic signals from barrels shots, whether a given barrel is suitable for operation or its wear exceeds the permissible level.

The mathematical formulation of the binary classification problem looks as follows. There is a set $X \in \mathrm{R}^m$ which is the space of objects (in our case, the objects are barrels described by informative signs of shots from them) and Y – a set of class names.

X is an m-dimensional vector:

$$\forall \in X : \mathbf{x} = (x^1, x^2, \ldots, x^m), \quad (3)$$

where $x^i \in \mathrm{R}^m, \forall i = \overline{1,m}$.

In our case, $m = \text{card}\left\{IS_i\right\} = 15$ is the dimension of the sign-oriented description of the acoustic parameters of each shot. The set of Y classes contains 2 elements – a serviceable barrel / an unserviceable barrel (formally described as 1 and –1), i.e. $Y = \{+1, -1\}$. There is some dependence $y : X \to Y$, the values of which are known only for the objects of the training sample $y_i = y^*(x_i)$. It is required to construct a classification algorithm $\alpha : X \to Y$, that extends this dependence to the entire space *X*. With this, it is required to minimize the number of errors made by the algorithm on the training sample.

Modern machine learning theory represents a wide range of information technology for classification tasks [30] it should be noted that the choice of classification technology is not a simple problem. In particular, Wolpert's No Free Lunch Theorem is well known [31], from which it follows that there is no universal classification algorithm. If the classification algorithm a_1 is more efficient than the a_2 algorithm in solving a certain problem, then there definitely should be a problem for which the a_2 algorithm is more efficient than the a_1 algorithm. To solve the problem, the support vectors machine (SVM) proposed by V. Vapnik [32] was chosen. Today SVM classifiers are rapidly gaining popularity, successfully competing with other verification methods, in particular with neural networks. This is evidenced, for example, by Google's citation information: as of 01.07.2020, the fundamental work of V. Vapnik [32] was cited in scientific publications 83327 times. SVM classifiers are characterized by fairly high resistance to the statistical characteristics of the original signs vectors. At the same time, SVM classifiers look more preferable in comparison, for example, with neural network classifiers – in practical implementation, instead of a multiextremal problem (with the probability of reaching a local extremum), they solve a quadratic programming problem that has a unique solution. In addition, the separating surfaces of the SVM classifier solutions have higher separating capabilities by maximizing the width of the separating strip. This makes such classifiers promising in terms of computational efficiency and accuracy. The essence of the SVM method is reduced to the problem of separating vectors by belonging to one of the two classes, i.e. to the problem of finding a separating hyperplane of dimension *(m-1)* [33]. For a two-dimensional case, the problem is usually considered graphically (*Fig.2*). Here, two-dimensional objects of classification of two different classes are conventionally shown in red and blue.

The purpose of the SVM algorithm is to construct a hyperplane based on data of the training sample that will separate the elements of the two classes in an optimal way (surface 1 in *Fig. 2*). There can be a set of separating hyperplanes, so it is necessary to choose one optimal one among them. To assess the optimality of a hyperplane, the concept of a "margin" is introduced [34]. This is a characteristic that evaluates how much an object is "immersed" in its class and how typical it is for such one. The smaller the margin value, the closer the object comes to the class boundary and the higher the probability of error becomes. The margin is negative if and only if the algorithm makes an error on the object. The way to construct it is to parallel shift the original hyperplane in both directions until it intersects the first vectors of each class. These positions of the hyperplane will be the boundaries of the margin. It is clear from *Fig. 2* that such a margin for any hyperplane can be constructed uniquely. When implementing the SVM method, it is believed that maximizing the margin between classes separated by a hyperplane contributes to a more confident classification. Such a hyperplane is called the optimal separating hyperplane.

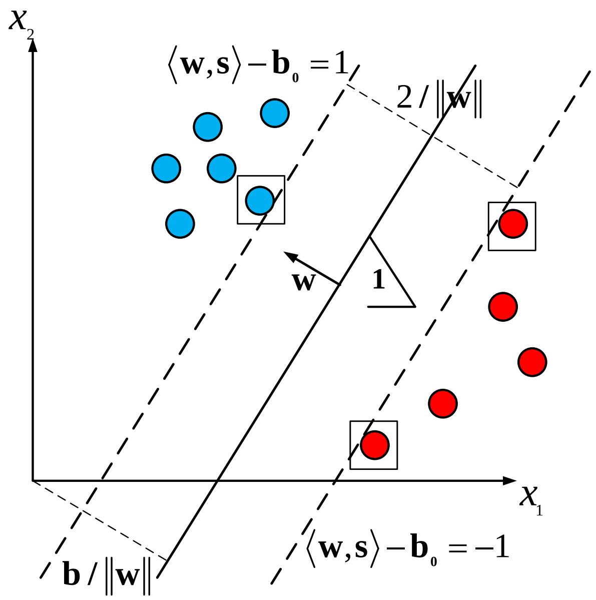

Fig. 2. **Graphical representation of the SVM classifier in two-dimensional space**

Let us denote the training data as:

$$\{\mathbf{x}_i, k_i\}, i = \overline{1, n}, k_i \in \{-1, +1\}, \tag{4}$$

where $\mathbf{x}_i$ – are the elements of the sign-oriented description.

Suppose that there is a hyperplane separating data of two classes (positive and negative).

Points $\mathbf{x}_i$, lying on the hyperplane satisfy the condition:

$$\langle \mathbf{w}, \mathbf{x} \rangle + b_0 = 0, \tag{5}$$

where: $\mathbf{w}$ – is the perpendicular to the separating hyperplane (*Fig. 2*);

b_0 – auxiliary parameter (shifting of the hyperplane relative to the origin);

$|b_0 / \|\mathbf{w}\||$ – perpendicular to the hyperplane, dropped from the origin.

Support vector machine constructs a classifying function F in the form

$$F(\mathbf{x}) = sign(\langle \mathbf{w}, \mathbf{x} \rangle + b_0. \tag{6}$$

Objects for which $F(\mathbf{x}) = 1$, fall into one class, and objects with $F(\mathbf{x}) = -1$ fall into another. Let $\mathbf{x}^+$ and $\mathbf{x}^-$ – be two points from different classes having the smallest distance from the separating hyperplane to the closest point of the corresponding class of the same name. It is believed that $\mathbf{x}^+$ and $\mathbf{x}^-$ lie on the border of the "separating" strip, the width of which is defined as $(\mathbf{x}^+ + \mathbf{x}^-)$. The problem of optimal separation in this case is reduced to finding "support" vectors and hyperplanes closest to the support vectors of two classes and parallel to the optimal separating hyperplane.

It can be shown that these hyperplanes are described by the equations:

$$\langle \mathbf{w}, \mathbf{x} \rangle + b_0 = 1 \text{ для } k_i = +1, \tag{7a}$$

$$\text{и } \langle \mathbf{w}, \mathbf{x} \rangle + b_0 = -1 \text{ для } k_i = -1. \tag{7b}$$

If the training sample is linearly separable, then the hyperplanes are chosen so that no points of the training sample lie between them, and then the distance between the hyperplanes (separating margin M in *Fig. 2*) is maximized.

For vectors belonging to different classes, the following restrictions are valid:

$$\langle \mathbf{w}, \mathbf{x} \rangle + b_0 \geq 1 \text{ для } k_i = +1, \tag{8a}$$

$$\text{и } \langle \mathbf{w}, \mathbf{x} \rangle + b_0 \leq -1 \text{ для } k_i = -1. \tag{8b}$$

The points satisfying inequality (8a) lie on the boundary of the strip H_1 with the normal line $\mathbf{w}$ perpendicular from the origin $1 - b_0 / |\mathbf{w}|$, and the points satisfying inequality (8b), lie on the boundary of the strip H_2 with the opposite normal line $\mathbf{w}$ and perpendicular from the origin $-1 - b_0 / |\mathbf{w}|$. They are called support vectors (in *Fig. 2* marked with squares). Thus, $^+\mathbf{x} = \mathbf{x}^- = 1 / \mathbf{w}$ and the width of the separating stripe is also equal to $2 / \mathbf{w}$ [34].

The construction of an optimal separating hyperplane is reduced to a quadratic programming problem, i.e. minimization of a quadratic form under n inequality constraints with respect to variables $\mathbf{w}$, b_0:

$$\begin{cases} \langle \mathbf{w}, \mathbf{w} \rangle \to \min, \\ k_i(\langle \mathbf{w}, \mathbf{x}_i \rangle - b_0) \geq 1, i = \overline{1, n} \end{cases}. \tag{9}$$

By the Kuhn-Tucker Theorem [35], this problem is equivalent to the dual problem of finding the calculus saddle point of the Lagrange function:

$$L(\mathbf{w}, b_0, \boldsymbol{\lambda}) = 0{,}5\langle \mathbf{w}, \mathbf{w}\rangle + \\ + \sum_{i=1}^{n} \lambda_i (k_i \langle \mathbf{w}, \mathbf{x}_i \rangle - b_0) - 1) \to \min_{\mathbf{w}, b_0} \max_{\lambda},$$

$$\lambda_i \geq 0, i = \overline{1,n}, \quad (10)$$

$$\lambda_i = 0{,}8;\, 8k_i(\langle \mathbf{w}, \mathbf{x}_i \rangle - b_0), i = \overline{1,n}, \quad (11)$$

where $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \ldots, \lambda_n)$ is the vector of dual variables.

In practice, cases of linear data separability by a hyperplane are quite rare. More often it is necessary to classify linearly inseparable objects (and the barrels classified in our task are no exception). To generalize the SVM algorithm to the case of linear inseparability, the assumption of the appearance of an insignificant amount of errors on the training objects (penalty) is introduced, which allows to soften the constraints (10–11). A set of additional variables $\xi_i \geq 0$ is introduced, characterizing the magnitude of the error of informative signs on the classified objects $\mathbf{x}_i, i = \overline{1,n}$. If $\xi_i = 0$, then there is no error on $\mathbf{x}_i$, if $0 < \xi_i < 1$, then the object $\mathbf{x}_i$ falls inside the separating strip, but is correctly classified by the support vector machine if an error is made in $\mathbf{x}_i$ [33].

With the introduced assumptions, system (9) can be rewritten as:

$$\begin{cases} 0{,}5\langle \mathbf{w}, \mathbf{w}\rangle + C\sum_{i=1}^{n} \xi_i \to \min_{\mathbf{w}, \mathbf{b}_0, \boldsymbol{\xi}}, \\ k_i(\langle \mathbf{w}, \mathbf{s}_i \rangle - \mathbf{b}_0 \geq 1 - \xi_i), i = \overline{1,n}, \\ \xi_i \geq 0, i = \overline{1,n} \end{cases}, \quad (12)$$

where C is the “control” parameter of the method, which allows to find a compromise between maximizing the separating strip and minimizing the total error.

The Lagrange function for this problem has the form:

$$L(\mathbf{w}, \mathbf{b}_0, \boldsymbol{\xi}, \lambda, \boldsymbol{\eta}) = 0{,}5\langle \mathbf{w}, \mathbf{w}\rangle - \\ - \sum_{i=1}^{n} \lambda_i (k_i(\langle \mathbf{w}, \mathbf{x}_i \rangle - b_0) - 1) - \\ - \sum_{i=1}^{n} \xi_i (\lambda_i - \eta_i - C), \quad (13)$$

where $\boldsymbol{\eta} = (\eta_1, \eta_2, \ldots, \eta_n)$ is the vector of variables, dual for $\boldsymbol{\xi} = (\xi_1, \xi_2, \ldots, \xi_n)$.

Another way to solve linearly inseparable problems is as follows. All elements of the training set are embedded in the space H of a higher dimension using a special mapping $krnl(\mathbf{s}_i)$. If the space H has a sufficiently high dimension, then there is a high probability that the sample in it will be linearly separable. In the space H vectors of the sign-oriented description of objects $\mathbf{x}_i$ are replaced by vectors $krnl(\mathbf{x}_i)$, and the construction of the support vector machine itself is carried out similarly to that described above [33].

In this case, the classifying function F takes the form:

$$F(\mathbf{x}) = sign(\langle \mathbf{w}, krnl(\mathbf{x})\rangle + b_0) . \quad (14)$$

The function $krnl(\mathbf{x}, \mathbf{x}')$ called the kernel of the classifier. From a mathematical point of view, the kernel can be any positive definite symmetric function of two variables. Positive definiteness is necessary for the corresponding Lagrange function in the optimization problem to be bounded from below, i.e. the optimization problem would be well defined. The accuracy of the classifier depends on the choice of the kernel. In practice, various kernels are most often used; the most popular is the kernel $krnl(\mathbf{x}, \mathbf{x}') = e^{-\gamma\|\mathbf{x}-\mathbf{x}'\|^2}, \gamma \geq 0$ or so-called Gaussian or radial kernel.

The very first attempts to separate the training set into barrels without wear and barrels with wear in our problem showed that the sets are not linearly separable, and then a Gaussian kernel was used, with which the sets were easily separated.

4.2.2. Data normalization

The SVM method is very sensitive to data scaling (normalization). If the data is not normalized, then the vector of signs with large deviations from the mean values of the coordinates will affect the classifier too much. Therefore, it is common practice to convert signs so that the final data presentation is more suitable for the correct operation of the classifier [34–35]. Indeed, in our case, the informative signs describing the state of the artillery barrel represent the values of physical quantities that are different in nature and dimension, the range of values of which is quite different. Analyzed 6 methods of normalization of data sets **X** [36] for subsequent SVM classification.

1) Normalization with zero means value

The zero mean normalization method is based on mean and standard deviation.

The standard deviation is calculated as follows:

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$$x_{std} = \left[\frac{1}{(N-1)} \sum_{i=1}^{N} (x_i - x_{mean})^2 \right]^{\frac{1}{2}}, \qquad (15)$$

where x_{mean} is a mean value.

$$x_i^{'} = \frac{x_i - x_{mean}}{x_{std}}.$$

2) Sigmoid normalization

Scaling non-linearly converts the input data to the-1 to 1 range using a sigmoid function:

$$x^{'} = \frac{1-e^a}{1+e^a}, \qquad (16)$$

where $a = \dfrac{x_i - x_{mean}}{x_{std}}$.

Data that is within the standard deviation of the mean is displayed in a nearly linear area. The outlier points, on the other hand, draw together along the tails of the sigmoidal function. Sigmoidal normalization is especially effective when you have outlier points that should be included in the dataset. This prevents the most common values from being compressed into considerably the same ones without losing the ability to store very large outliers.

3) Softmax normalization

The method "softly" tends to its maximum and minimum values, never reaching them:

$$x_i^i = \frac{1}{1+e^{-a}}, \qquad (17)$$

where *a* is the same as in expression (15).

The transformation is relatively linear in the midrange and has smooth non-linearity at both ends. The full range of the output data is from 0 to 1, and the transformation ensures that none of the values are outside this range.

4) Minmax normalization

The transformation performs a linear transformation of the original data x into a specified interval $(New_{\min}, New_{\max})$:

$$x_i = New_{\min} + (New_{\max} - New_{\min}) \cdot \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, \qquad (18)$$

$$x_{\max} = \max_{1 \le i \le N} x_i, x_{\max} = \min_{1 \le i \le N} x_i. \qquad (19)$$

This method scales the data from $(x_{\min}, x_{\max})$ to $(New_{\min}, New_{\max})$ proportionally. The advantage of this method is that it accurately preserves all data value relationships. This scaling is useful when the sign values are significantly greater than 1 in absolute value.

5) Decimal normalization

Normalization is done by moving the decimal point. The number of decimal places to move depends on the maximum absolute value. This type of scaling converts the data to the interval [-1, 1]. Conversion formula:

$$x_i^{'} = \frac{x_i}{10^j}, \qquad (20)$$

where *j* is the smallest integer, such what $\max(|x_i^{'}| < 1)$. This scaling is useful when feature values are significantly greater than 1 in absolute value.

6) Normalization by max value

In this method, the normalization equation is:

$$x_i = \frac{x_i}{x_{\max}}, x_{\max}, x_{\max} = \max_{1 \le i \le N} x_i. \qquad (21)$$

When the maximum positive value is too small and the minimum negative value is too small, for example, the range of values for a characteristic (0.1; -10), you can increase the difference, but the range of normalized values can be larger.

All normalization methods are verified for classification error and counting time by cross-validation on a sample of data. The results are shown in *Table 1.*

Before classification, minmax normalization was further used as providing the best classification.

Table 1. **Comparative analysis of performance normalization methods**

##	Normalization method	Probability of correct classification	Counting time, s
1	*No normalization*	0.58	0
2	*Normalization with zero mean value*	0.67	38.8
3	*Sigmoid normalization*	0.65	4.2
4	*Softmax normalization*	0.62	37.7
5	*Minmax normalization*	0.73	25.4
6	*Decimal scaling*	0.64	22.0
7	*Normalization by max value*	0.71	26.5

4.2.3. Optimization of SVM classifier hyperparameters

The two parameters C and γ, introduced above, called hyperparameters, must be optimized before training the support vector machine. These values are critical to the accuracy of the classification algorithm [39–41]. Various strategies are possible to optimize parameter selection. The easiest approach is a simple grid search. A two-dimensional grid is set, at each grid point SVM training is performed on the training dataset and the trained machine is applied to an independent sample of test data, in which some indicator is estimated. For each point on the grid, the learning problem is solved using the training sample and the classification error is calculated on the control (test) sample 1_K.

The (C,γ)-pair with the highest accuracy is selected. This procedure is called cross-validation or cross-validation (CV) [42]. Below we use the term CV-procedure.

To select C and γ using a K-fold CV-procedure the entire training dataset is split into K equal (up to 1) parts (K-fold cross-validation). The number of training iterations in this algorithm corresponds to the number of K blocks. One test block is used as testing data, and at each iteration, the classification error is estimated using the remaining (K-1) blocks as a training set. An (C,γ)-pair with the minimum error $\underset{i=1.K}{\operatorname{argmin}} E_i \Rightarrow (C,\gamma)_{opt}$, is selected, and this pair is then used to test and classify new data on the entire set of work of the SVM classifier [42] The scheme of the procedure is shown in *Fig.3*.

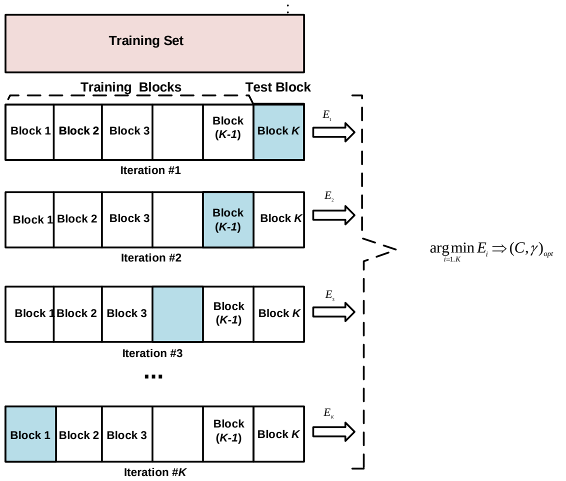

Fig. 3. **Scheme of hyperparameters optimization by the cross-validation method**

The study used Leave-one-out CV (LOOCV) [42–43], which is the described procedure of the same as the K-block cross-validation, but in this case the test sample is used one element (instance), i.e. K is equal to the total number of elements. The main disadvantage of cross-validation, especially Leave-one-out type, is the increased amount of computation. Since K classifiers are trained instead of one, cross-validation will be about K times slower than splitting the data once. But on the other hand, the quality of training significantly increases, since the SVM classifier "gains a margin of safety" for the correct classification of an object that is absent in the training sample. Due to the high complexity of CV procedures, gread search is usually used [44–45], usually with exponential growth of C and γ. The block diagram of the CV procedure algorithm is shown in *Fig. 4*. The exponential grid is used to reduce the computational time, since the exhaustive method with training at each step requires a lot of time. To improve the accuracy of the selection of hyperparameters, a two-stage CV method was applied.

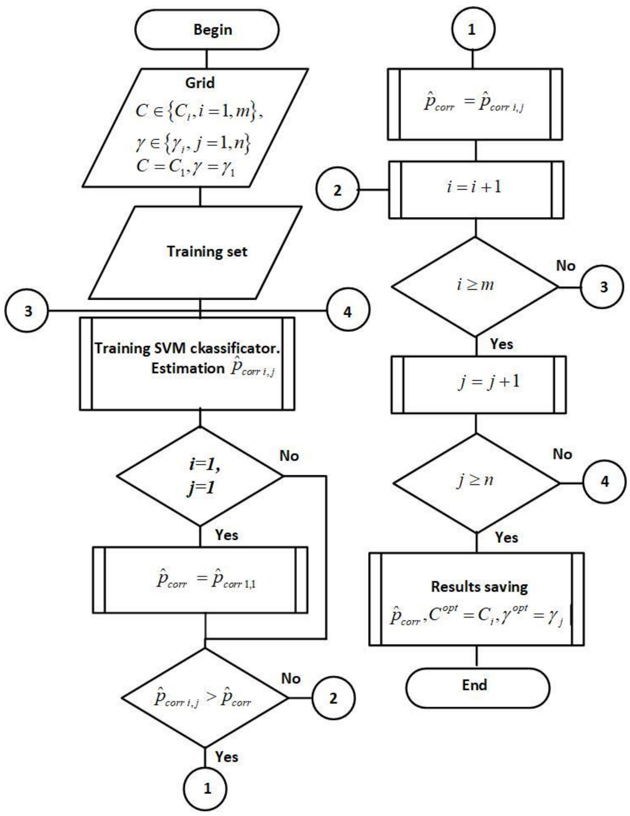

Fig. 4. **Block diagram of the cross-validation algorithm for choosing the optimal hyperparameters**

At the first stage, the hyperparameters are selected on a decimal exponential grid, C in the range $\{10^c, ... ,10^d\}$, and γ in the range $\{10^e, ... ,10^f\}$. At the second stage, the hyperparameters are sorted out on a linear grid with a small step in the vicinity of the pair of optimal values selected at the first

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stage. The results of the first stage of hyperparameter optimization are shown in *Fig. 5*.

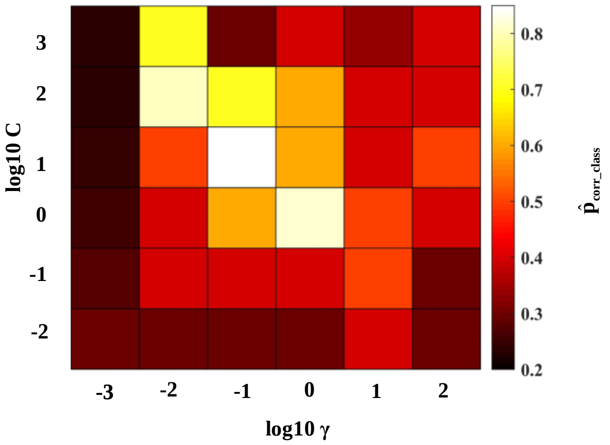

Fig. 5. **The result of the first stage of selection of hyperparameters C and γ**

As a result of searching on a decimal exponential grid, the best classification result equal to $\hat{p}_{corr}$ =0,71, is provided for $C^{(1)}_{opt}$ =10, $\gamma^{(1)}_{opt}$ =0,1. At the second stage, a grid of linear scale $C \in [C^{(1)}_{opt} - C^{(1)}_{opt}/2, C^{(1)}_{opt} + C^{(1)}_{opt}/2]$, $\gamma \in [\gamma^{(1)}_{opt} - \gamma^{(1)}_{opt}/2, \gamma^{(1)}_{opt} + \gamma^{(1)}_{opt}/2]$ was built, with a step of ΔC =0,1 and $\Delta\gamma$ =0,01. As a result, the optimal values of hyperparameters $C^{(2)}_{opt}$ =12,4 and $\gamma^{(2)}_{opt}$ =0,17, were selected, providing the correct classification with probability $\hat{p}_{corr}$ =0,93 on the complete training and test samples.

The conducted research made it possible to formulate **a method for the binary classification of artillery barrels by the level of wear in the following way**.

Step 1. Formation of a classified set of records of acoustic signals from shots from barrels with different levels of wear *S_Records***.**

Step 2. Selecting SW and MW signals in each record $s_{sw}(t), s_{mw}$ respectively.

Step 3. Formation of a set of informative signs for classification, based on the classified set of SW and MW signals

$$\{IS_i\} = \{IS^{time}_{SW,i}\} \cup \{IS^{freq}_{SW,i}\} \cup \{IS^{freq\_cum}_{SW,i}\} \cup \cup \{IS^{time}_{MW,i}\} \cup \{IS^{freq}_{MW,i}\} \cup \{IS^{freq\_cum}_{MW,i}\},$$

$\operatorname{card}\{IS_i\} = 15$.

Step 4. Formation of a classified sample of informative signs for training and testing the SVM classifier $\mathbf{X} = \{\mathbf{x}^{(s)}_1, \mathbf{x}^{(s)}_2, \dots, \mathbf{x}^{(s)}_m, \mathbf{x}^{(w)}_1, \mathbf{x}^{(w)}_2, \dots, \mathbf{x}^{(w)}_m\}$.

Step 5. Partitioning the classified sample of informative signs into training and test ones $\mathbf{X} = \mathbf{XC} \cup \mathbf{XT}$.

Step 6. Training the SVM classifier on the training set $\mathbf{XC}$ of informative signs with a Gaussian kernel

$krnl(\mathbf{x}, \mathbf{x}') = e^{-\gamma\|\mathbf{x}-\mathbf{x}'\|^2}$, $\gamma = 1/2\sigma^2, \sigma \ge 0$.

Step 7. Testing the classifier on a test sample $\mathbf{XC}$.

Step 8. Optimization of the SVM classifier by adjusting the hyperparameters (C, γ) using a two-stage cross-validation method.

Step 9. Classification of barrels according to incoming records (with repetition of Steps 1–3) by a trained and optimized SVM classifier.

Step 10. Return to Step 1, followed by repeating steps 6–8 for additional training of the classifier.

4.3. Information technology (IT) and an automated system for technical diagnostics of the state of barrels based on a set of acoustic informative signs

The research carried out made it possible to construct an IT for technical diagnostics of the state of the barrels by a set of informative signs. The IT diagram is shown in *Fig. 6*.

Information technology has three stages. At stage 1, data is prepared for building an automatic classifier. In the process of artillery firing, N records of acoustic signals from shots from cannons of this type are recorded.

The records are classified, i.e. for each entry, the category of the barrel from which the shot was fired is indicated: “barrel without wear / barrel with wear”. Records of classified signals are saved in the “Signal Records” database (DB). Then, a shock wave (SW) and a muzzle wave (MW) signals are highlighted in each of the N records.

Three sets of signs are generated for each entry: informative signs (IS) of SW and MW in the time domain $\{IS^{time}_{BW+MW,i}\}, i = 1, N$, informative signs of SW and MW in the frequency domain $\{IS^{freq}_{BW+MW,i}\} i = 1, N$ and cumulant informative signs of SW and MW $\{IS^{cum}_{BW+MW,i}\} i = 1, N$. A common sign-oriented description for each barrel is formed from the three IS sets

$$\mathbf{X} = \{IS^{time}_{BW+MW,i}\} i = 1, n \cup \{IS^{freq}_{BW+MW,i}\} i = 1, n \cup \cup \{IS^{cum}_{BW+MW,i}\}, i = 1, N.$$

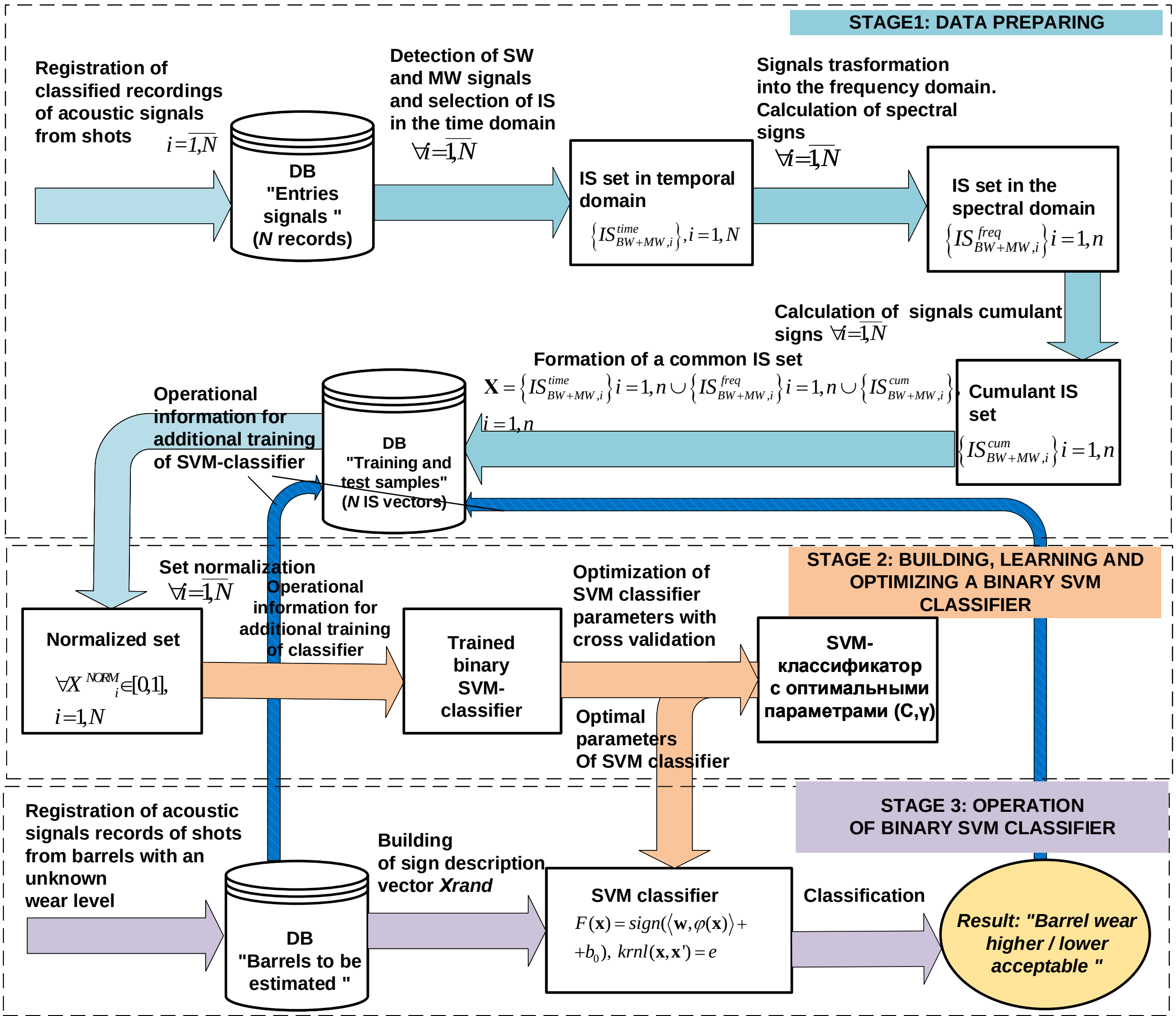

Fig. 6. **General scheme of information technology for technical diagnostics of the state of barrels by a set of informative signs**

Sign-oriented descriptions are saved in the “Training and test samples” database containing N vectors of IS. At stage 2, the construction, training and optimization of the binary SVM classifier is carried out. Sign-oriented descriptions are normalized by the minmax method, resulting in a normalized sample of IS $\forall X^{NORM}_{i} \in [0,1], i = 1, N$. This sample is divided into training and test ones. An SVM classifier is constructed, which is then trained using a test sample. At the next stage, using the two-stage grid search method, the hyperparameters of the SVM classifier C and γ are optimized by the cross-validation method. As a result, we get a trained SVM classifier with optimized parameters. The final parameters of the SVM classifier are remembered for use at the next stage. At stage 3 of this information technology, the actual operation of the binary SVM classifier is carried out. The next record of acoustic signals from a shot from a barrel with an unknown level of wear is registered and saved in the “Barrels to be evaluated” database. The vector of its sign-oriented description X_{rand} is constructed and presented for classification. The SVM classifier makes a decision: “Barrel wear is higher / lower than acceptable” according to rule

$$F(\mathbf{x}) = sign(\langle \mathbf{w}, krnl(\mathbf{x})\rangle + b_0), \quad krnl(\mathbf{x},\mathbf{x}') = e^{-\gamma\|\mathbf{x}-\mathbf{x}'\|^2}.$$

Due to the strong variability of the surface atmospheric transmission channel during operation, the SW and MW signals with ISs, that are very different from those on which it was trained, can arrive at the input of the classifier. Therefore, IT provides for constant replenishment of the “Training and test sample” database and constant additional training of the SVM classifier after every 10 new records are received.

On the basis of IT, an automated system for technical diagnostics of the state of artillery barrels was developed using a set of informative signs (*Fig. 7*).

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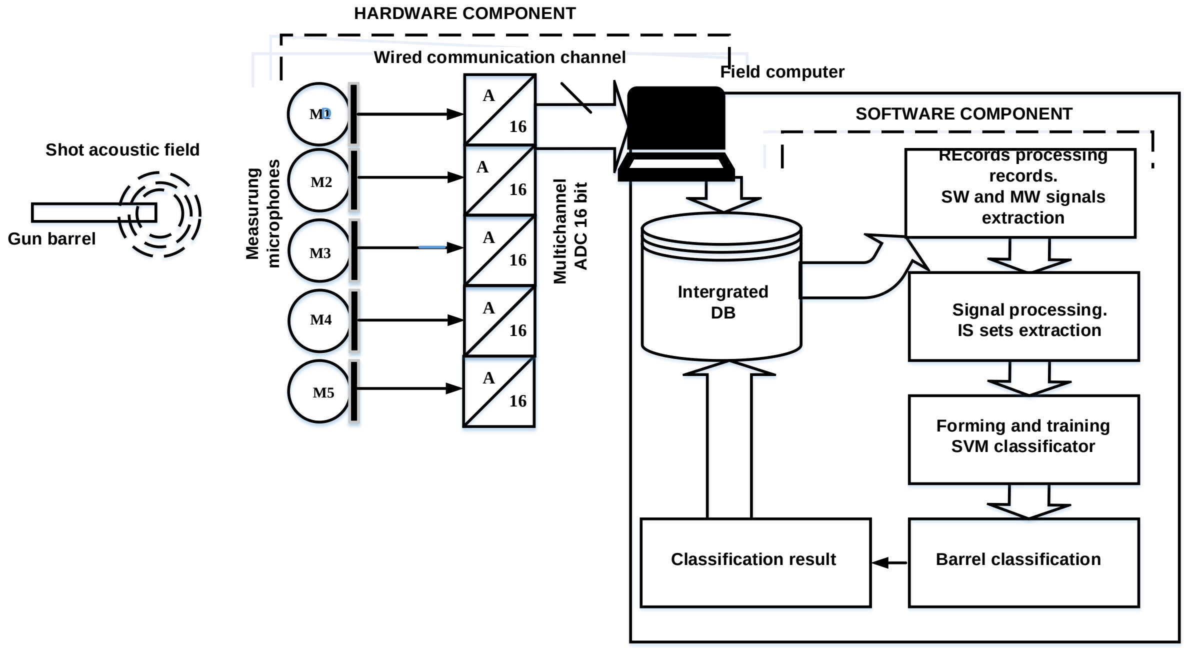

Fig. 7. **Automated system for technical diagnostics of barrels' condition based on a set of informative signs**

An automated system consists of hardware and software components. The hardware component includes 5 microphones (M1, …, M5) that register acoustic fields that arise during a shot. The signals from the outputs of the microphones are converted into digital form using a 5-channel 16-bit analog-to-digital converter (ADC) and are fed to the input port of the computer via a wired communication channel.

The computer itself is a rugged laptop. Further processing of the measurement information is carried out by a software component.

The software component includes:

– an integrated database,

– programs for processing records and signals, identifying and accumulating informative signs,

– trained SVM classifier.

5. FULL-SCALE EXPERIMENT FOR DIAGNOSING THE STATE OF THE CANALS OF ARTILLERY BARRELS BY ACOUSTIC FIELDS OF SHOTS

A full-scale field experiment was carried out on real acoustic signals recorded during training firing of 152 mm 2A36 "Hyacinth-B" towed cannons.

Figure 8 shows the hardware component of the prototype of the automated system, which in the experiment was provided by two measuring condenser microphones of the Rode NT1-A and Rode NT-USB types connected to a MacBook Pro computer (MacOS Catalina v10.15.5, CPU: Intel Core i7 2.2 GHz , RAM: 16Gb) via a multichannel 16-bit TASCAM 102i ADC.

Fig. 8. **Hardware component of the automated system located at the firing position**

The purpose of the experiment was to experimentally confirm the correctness of the main research results, in particular, the possibility of a confident classification of artillery barrels according to the level of their wear on the basis of measuring and evaluating the SW and MW parameters.

In the experiment, shots were fired from two cannons: Cannon No. 1, from which 91 shots were previously fired, i.e. a cannon with a practically new barrel, and Cannon No. 2, from which 1968 shots were fired earlier, i.e. cannon with a barrel of very high wear level. The results of the field experiment are shown in *Table 2.* The data in the table demonstrates the following:

Table 2. ***Results of a full-scale field experiment***

Indicator name, units	Values			
1. Experiment number	1	2	3	4
2. The total number of shots fired earlier from the cannon (No. of each one)	91, (No. 1)		1968, (No. 2)	
3. Number of a shot from cannon	1	2	1	2
4. Distance from cannon to measuring microphone, m	300			
5. Tabular firing range at sight, m	9000			
6. Total correction for meteorological conditions, m	-137	-157	-215	-215
7. Ballistic corrections, m	+12			
8. Estimated firing range, m	8875	8855	8797	8797
9. Actual firing range, determined by the rangefinder, m	9165	9082	8665	8671
10. Amplitude of shock waves, Pa	380		240	
11. Duration of shock wave signal, ms	4.8		4.1	
12. Amplitude of the muzzle wave, Pa	140		90	
13. Duration of the first half-period of the muzzle wave, ms	22		14	
14. Spectrum width at the level of 0.707 shock wave signal, Hz	180		250	
15. Center frequency (maximum frequency) of the muzzle wave signal spectrum, Hz	12		16	
16. Estimated initial speed of shell, m/s	560			
17. Calculated real muzzle velocity, m/s	558.2	556.9	504.2	504.5

– Shooting from a barrel with high wear is, as expected, less effective (the actual firing range is significantly less than the calculated one).
– The muzzle velocity of a shell fired from a worn barrel is noticeably lower than a shell fired from a barrel without wear.
– Informative signs of SW and MW, both in the time and in the frequency domain, differ significantly, which allows them to be separated for training an automated classifier.

Thus, a full-scale field experiment confirmed the correctness of the main scientific and technical solutions obtained in the process of research.

6. CONCLUSIONS

An SVM classifier has been built, which allows classifying artillery barrels by the level of wear on the basis of a training classified sample of informative signs of acoustic signals of shock and muzzle waves. The optimal methods for the normalization of informative signs have been studied and chosen. The process of adjusting an SVM classifier by optimizing hyperparameters using Leave-one-out cross-validation has been investigated. A method has been developed for the binary classification of artillery barrels by wear level.

The information technology has been developed for diagnosing the state of artillery barrels based on a set of informative signs, which consists of the following stages: Data preparation; Building, training and optimization of a binary SVM classifier; Operation of a binary SVM classifier. On the basis of IT, an automated system for technical diagnostics of the state of artillery barrels has been developed based on a set of acoustic informative signs. A computational model experiment has shown that the use of the developed automated system using a classifier trained on a consistent classified sample makes it possible to obtain an indicator of the correct classification of artillery barrels according to the degree of wear, equal to 0.94. A full-scale field experiment confirmed the correctness of the basic scientific and technical solutions that form the basis of information technology and an automated diagnostic system.

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ІНФОРМАЦІЙНА ТЕХНОЛОГІЯ АВТОМАТИЗОВАНОЇ ОЦІНКИ ЗНОСУ АРТИЛЕРІЙСЬКИХ СТВОЛІВ НА ОСНОВІ SVM-КЛАСИФІКАТОРА

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АНОТАЦІЯ

Розроблено інформаційну технологію автоматизованої оцінки рівня зносу артилерійських стволів. Інформаційна технологія заснована на аналізі акустичних полів, які супроводжують постріл. Акустичне поле пострілу складається з балістичної хвилі, що супроводжує вилітаючий з надзвуковою швидкістю снаряд, і дульної хвилі, що утворюється при викиді зі стволу порохових газів. Параметри балістичної і дульної хвиль істотно залежать від рівня зносу стволу. Це дає можливість побудувати автоматичний класифікатор стволів за рівнем зносу на підставі аналізу інформативних ознак акустичних сигналів, зареєстрованих мікрофонами поблизу вогневої позиції гармати. В основу інформаційної технології покладено бінарний SVM-класифікатор. Синтезовано набір записів акустичних полів пострілів на основі реальних сигналів, зареєстрованих при стрільбі 155 мм гаубиці. З набору записів сформовані навчальна і тестова вибірка інформаційних ознак для навчання класифікатора і оцінки його якості. Досліджено методи попередньої нормалізації даних навчальної та тестової вибірок. Розроблено методику оптимізації гіперпараметрів класифікатора шляхом поекземплярної крос-валідації. Методика являє собою двоетапний пошук оптимальних значень гіперпараметрів. На першому етапі пошук здійснюється на експоненційній десяткової сітці. На другому етапі оптимальні значення гіперпараметрів уточнюються на лінійній сітці. Сформульовано метод бінарної класифікації артилерійських стволів за рівнем зносу. Перевірка класифікатора на спроможній тестової вибірці показала, що він забезпечує правильну класифікацію зносу стволів з ймовірністю 0,94. Розроблено інформаційну технологію класифікації артилерійських стволів за рівнем зносу на підставі аналізу акустичних полів пострілів. Інформаційна технологія складається з трьох стадій: підготовка даних, побудова, навчання і оптимізація бінарного SVM-класифікатор і експлуатація бінарного SVM-класифікатор. Проведено польовий експеримент, що підтвердив правильність основних наукових і технічних рішень. Розроблено автоматизовану систему для класифікації стволів за рівнем зносу.

Ключові слова: артилерійський ствол; рівень зносу; балістична хвиля; дулова хвиля; бінарний SVM-класифікатор; інформаційна технологія

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ИНФОРМАЦИОННАЯ ТЕХНОЛОГИЯ АВТОМАТИЗИРОВАННОЙ ОЦЕНКИ УРОВНЯ ИЗНОСА АРТИЛЛЕРИЙСКИХ СТВОЛОВ НА ОСНОВЕ SVM-КЛАССИФИКАТОРА

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АННОТАЦИЯ

Разработана информационная технология автоматизированной оценки уровня износа артиллерийских стволов. Информационная технология основана на анализе акустических полей, сопровождающих выстрел. Акустическое поле выстрела состоит из баллистической волны, сопровождающей вылетающий со сверхзвуковой скоростью снаряд, и дульной волны, образующейся при выбросе из ствола пороховых газов. Параметры баллистической и дульной волн существенно зависят от уровня износа ствола. Это дает возможность построить автоматический классификатор уровня износа стволов на основании анализа информативных признаков акустических сигналов, зарегистрированных микрофонами вблизи огневой позиции орудия. В основу информационной технологии положен бинарный SVM-классификатор. Синтезирован набор записей акустических полей выстрелов на основе реальных сигналов, зарегистрированных при стрельбе 155 мм гаубицы. Из набора записей сформированы обучающая и тестовая выборка информационных признаков для обучения классификатора и оценки его качества. Исследованы методы предварительной нормализации данных обучающей и тестовой выборок. Разработана методика оптимизации гиперпараметров классификатора путем поэкземплярной кросс-валидации. Методика представляет собой двухэтапный метод поиска оптимальных значений гиперпараметров. На первом этапе поиск осуществляется на экспоненциальной десятичной сетке. На втором этапе оптимальные значения гиперпараметров уточняются на линейной сетке. Сформулирован метод бинарной классификации артиллерийских стволов по уровню износа. Проверка классификатора на состоятельной тестовой выборке показала, что он обеспечивает правильную классификацию износа стволов с вероятностью 0,94. Разработана информационная технология классификации артиллерийских стволов по уровню износа на основании анализа акустических полей выстрелов. Информационная технология состоит из трех стадий: подготовка данных, построение, обучение и оптимизация бинарного SVM-классификатора и эксплуатация бинарного SVM-классификатора. Проведен полевой эксперимент, подтвердивший правильность основных научных и технических решений. Разработана автоматизированная система для классификации стволов по уровню износа.

Ключевые слова: артиллерийский ствол; уровень износа; баллистическая волна; дульная волна; бинарный SVM-классификатор; информационная технология

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