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HIDDEN MARKOV MODELS OF TECHNICAL CONTROL OF TECHNICAL CONDITION PARAMETERS OF SELF-PROPELLED SPRAYERS

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Abstract. The main indicator used to study the reliability are hidden Markov models of technical control of the technical condition of self-propelled sprayers, which means the probability that the self-propelled sprayer will be operational at any time, except for planned periods during which the use of self-propelled sprayers is expected. Derivation of the analytical expression for hidden Markov models of technical control of the parameters of the technical condition of self-propelled sprayers - a rather time-consuming operation. The complexity increases with the complication of the graph, ie in an effort to take into account more technical conditions, factors that affect the process of technical control of self-propelled sprayers. Therefore, it is advisable to solve the problem of such a plan using a simulation model. Using the Stateflow modeling tool of the Matlab software package, a model has been developed that allows modeling discrete-event models. Model of self-propelled sprayers among Stateflow for estimating the coefficient of readiness during technical control of programs. The results of simulation are the values of hidden Markov models of technical control of the parameters of the technical condition of self-propelled sprayers in various technical control programs, which allows us to draw conclusions about the impact of technical control of self-propelled sprayers on the readiness factor.The probabilities of errors varied from 0 to 1, which is quite justified in cases where the technical control differs only in the place of measurement of the parameter of technical condition, and the means of measurement are the same. The author found that the readiness factor is sensitive to errors of the second kind in this case. Ways of further research are found in the study of other programs of technical control of self-propelled sprayers, in which the readiness factor is sensitive to the probability of errors of the first kind.

Key words: simulation model, coefficient of readiness, self - propelled sprayer, technical control.

Introduction

The analysis of periodic signals of complex shape is often carried out by decomposing it into harmonics in a Fourier series.

After analog-to-digital conversion, a continuous signal is represented by a set of its instantaneous values-samples. In practice, the Fast Fourier Transform is more common.

Formulation of problem

The essence of this transformation lies in the recurrent application of the fundamental expression of the discrete Fourier transform to the analyzed signal. There are different algorithms for the fast Fourier transform, which differ in the ways of dividing the samples into subgroups and the requirements for the number of samples to be processed. The Fourier transform transforms the original signal from the amplitude-time space into the frequency-time, and in the time domain - a linear signal prediction that describes the acoustic signal using an autoregressive model. The principle of the linear prediction method is described in the literature.

Analysis of recent research results

Suppose that there is a sequence of signal vectors $S(n)$ and a filter of order M, with an impulse response $A(z)$, whose time samples will be denoted by $a_i, i = 1, \dots, M$. The results of filtering the signal $S(n)$ by the filter $A(z)$ can be written:

$$e(n) = \sum_{i=0}^{M} a_i S(n-1) = S(n) + \sum_{i=0}^{M} a_i S(n-i) = S\grave{}(n) - S(n)$$

In this case, the values of $S(n)$ must be considered as an estimate of the value of $S\grave{}(n)$, built on the basis of the values of previous readings, and the value of $e(n)$ – as the value of the prediction error.

The next step is to solve the problem of optimizing the values of the coefficients in such a way that the error value $e(n)$ would be minimal. As an optimality criterion, the sum of the squares of the error values on the studied interval is used. In this case, the values of the optimized quantity are found as follows:

$$a = \sum_{n=n_0}^{n_i} e^2(n) = \sum_{n=n_0}^{n_i} \left[\sum_{i=0}^{M} a_i S(n-i)\right]^2 = \sum_{n=n_0}^{n_i} \sum_{i=0}^{M} \sum_{j=0}^{M} a_i S(n-i) a_i S(n-j)\, a_j$$

where n_0 and n_i – boundaries of the analysis interval. If you enter the notation:

$$c_{ij} = \sum_{n=n_0}^{n_i} S(n-i)S(n-j)$$

then the expression for the root-mean-square error can be written as:

$$a = \sum_{i=0}^{M} \sum_{j=0}^{M} a_i c_0 a_j$$

Differentiating this expression with respect to a_k allows us to obtain a system of linear differential equations, the solution of which will be the optimal value of the filter coefficients.

Another way to analyze signals is to study the spectrum. Traditionally, to use this method, the Fourier transform of the signal is used. This analysis is based on the calculation of a certain number of coefficients of the Fourier series of the periodic function $f(t)$:

$$f(t) = \sum_{n=-\infty}^{\infty} c_k e^{int}$$

This function is obtained from the original signal by smoothing, averaging in a certain way selected segments. The nature of the change in the coefficients gives valuable information about the properties of the signal, allows you to identify hidden periods. To calculate the coefficients, there is a fast algorithm that requires $NlogN$ operations, where N – the signal length.

An important property of the Fourier coefficients is that each of them reflects the behavior of $f(t)$ as a whole. The Fourier spectrum shows the global properties of signals, but it is difficult to extract information about local features from them – sharp jumps, narrow peaks, etc.

The reason for this lies in the structure of the e^{int} basis functions. These functions are stretched over the entire interval of change of the analyzed function, then the coefficients have the form:

$$c_n = (2\pi)^{-1} \int_0^{2\pi} f(t) e^{-int} dt$$

Fourier analysis provides good results when considering stationary signals, but when considering non-periodic signals, non-stationary processes, difficulties arise. The generalized spectral characteristic of the process as a whole makes it possible to determine the moments of occurrence of local changes in the signal, the appearance or disappearance of individual harmonics, but Fourier analysis does not make it possible to determine the local time-frequency bursts of the signal, i.e. simultaneously represent the signal in both time and frequency. Wavelet analysis solves this problem.

For both the Fourier transform and the construction of the basis of the wavelet transform, one function is used, called the mother wavelet. Thus, we can conclude that, unlike the traditional Fourier transform used for signal analysis, the wavelet signal transform provides a two-dimensional sweep of the signal under study. In this case, the frequency and coordinate are considered as independent variables. As a result, it becomes possible to analyze the properties of the signal simultaneously in the physical (time coordinate) and frequency spaces. The wavelet transform has the property of linearity, the essence of which is that the wavelet transform of a vector function is a vector with wavelet transform components of each component of the analyzed vector separately. The result of wavelet analysis is shift invariant, i.e. a signal shift in time by t_0 leads to a wavelet spectrum shift also by t_0. Invariance with respect to scaling means that stretching (compression) of the signal leads to stretching (compression) of the wavelet spectrum of the signal.

It follows from this that it makes no difference whether to differentiate the function or the analyzing wavelet. If the analyzing wavelet is given by a formula, then it can be very useful for signal analysis. It is possible to analyze high-order features or small-scale variations of the signal $s(t)$ while ignoring large-scale polynomial components (trend and regional background) by differentiating the required number of times either the wavelet or the signal itself. This property is especially useful when the signal is given as a discrete series.

Purpose of research

Purpose of research is a viscount description of the analytical position of the estimation of hidden Markov models of technical control of the parameters of the technical condition of self-propelled sprayers.

Research results

In the general case, wavelets include localized functions that are constructed from a single parent wavelet $\varphi(t)$ by shifting in time b and changing the time scale a:

$$\varphi_{ab}(t) = (|a|)^{-1/2} \varphi\left(\frac{t-b}{a}\right), (a,b) \in R, \varphi(t) \in L^2(R)$$

where the factor $(|a|)^{-1/2}$ ensures that the norm of the functions is independent of the scaling number a.

The continuous wavelet transform of the signal $s(t) \in L^2(R)$, which is used for qualitative time-frequency analysis, corresponds in meaning to the Fourier transform with the replacement of the harmonic basis e^{-int} by the wavelet one $\varphi\left(\frac{t-b}{a}\right)$:

$$W(a,b) = \langle s(t), \varphi_{ab}(t)\rangle = (|a|)^{-1/2} \int_{-\infty}^{\infty} s(t) \varphi\left(\frac{t-b}{a}\right) d, (a,b) \in R, a \neq 0$$

For quantitative methods of analysis (decomposition of signals with the possibility of subsequent linear reconstruction of signals from processed wavelet spectra), strictly from mathematical positions, any localized functions $\varphi(t) \in L^2(R)$, can be used as wavelet bases, if there are functions for them twins (pair functions) $\varphi^{\#}(t)$, such that the families $\{\varphi_{ab}(t)\}$ и $\{\varphi^{\#}_{ab}(t)\}$ can form paired bases of the function space $L^2(R)$. Wavelets defined in this way allow us to represent any arbitrary function in the space $L^2(R)$ as a series:

$$s(t) = \sum_{a,b} C(a,b)\,\varphi^{\#}_{ab}(t), (a,b) \in I$$

where the coefficients $C(a,b)$ – are the projections of the signal onto the wavelet basis of the space, which are determined by the scalar product:

$$C(a,b) = \langle s(t), \varphi_{ab}(t)\rangle = \int_{-\infty}^{\infty} s(t)\varphi_{ab}(t)dt$$

If the wavelet $\varphi(t)$ has the property of orthogonality, then $\varphi^{\#}(t) \equiv \varphi(t)$ and the wavelet basis is orthogonal. a wavelet can be non-orthogonal, but if it has a twin, and the pair $\varphi(t)$, $\varphi^{\#}(t)$ makes it possible to form families $\{\varphi_{mk}(t)\}$ и $\varphi^{\#}_{zp}(t)$, satisfying the biorthogonality condition on integers I:

$$\langle \varphi_{mk}(t), \varphi^{\#}_{zp}(t)\rangle = \delta_{mz} \cdot \delta_{kp}, m, k, z, p \in I$$

then it is possible to decompose the signals into wavelet series with the construction of an inverse reconstruction formula. Most of the restrictions imposed on wavelets are related to the accuracy of the inverse wavelet transform.

The results of the wavelet transform, as the scalar product of the wavelet and the signal function, contain combined information about the analyzed signal and the wavelet itself. Obtaining certain objective information about the analyzed signal is based on the properties of the wavelet transform, common to wavelets of all types.

The disadvantage of wavelet analysis is the need to select basis functions for a specific signal under study, which will better reflect its properties. For in-depth study of a specific signal, this device is indispensable, but to create a universal method for processing audio signals for mathematical modeling of the state of various technical objects, it is more expedient to use Fourier analysis.

The task of recognizing acoustic signals is to select the optimal probability distribution law that best suits the sound being processed. Based on the analysis of articles by leading world scientists, we can conclude that at the moment the most promising systems for recognizing acoustic signals based on several basic approaches (Fig. 1): neural networks, hidden Markov models, dynamic programming.

The goal of dynamic programming is to find the optimal non-linear matching of two segments of sound. In this regard, algorithms based on the works of R. Bellman have found wide application. This method compares a sound fragment with a pre-recorded sound standard. For this purpose, it is necessary to compare the segments corresponding to the same acoustic signals by means of deformation of the time axis, measure the remaining difference, and sum up these partial distances taken with certain weight coefficients. The key disadvantage of the dynamic programming approach is its binding to a specific technical object from which the audio signal is recorded. To determine the state of a similar technical object, it is necessary to first add sound standards to the system, which greatly increases the complexity of creating systems for determining the state of a technical object based on the analysis of an acoustic signal.

The use of neural networks for recognition of acoustic signals is a promising area of artificial intelligence. With a correctly specified structure, a neural network trained on a training set of acoustic signal data produces the correct recognition results when given to the input data belonging to the same set, but not used in the learning process. In practice, neural networks are used that include one or more hidden layers of neurons. The complexity of the network is determined based on the number of neurons in the hidden layers, since the number of neurons in the input and output layers is clearly fixed.

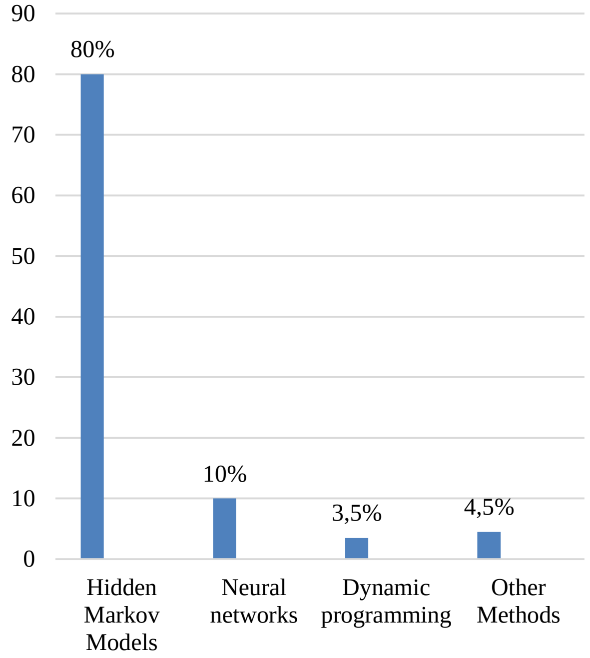

Fig. 1. Basic approaches to the recognition of acoustic signals.

The inputs of neural networks are vectors of signs of acoustic signals, and the outputs of the network are associated with sound standards, while the number of outputs is related to the number of recognizable sound signals. Neural networks are able to learn on acoustic signals from several identical sources, as a result, it is possible to develop a system that is independent of the sound source. Since when recognizing the sound signals of technical objects, the duration of the sound, and, accordingly, the number of feature vectors, is not known in advance, the task of training the neural network becomes much more complicated. Sometimes neural networks are used in combination with hidden Markov models. Despite their high potential, neural networks have not yet been widely used in the field of signal recognition, since their training is a complex process and requires a lot of computing power.

The use of hidden Markov models is currently the most promising and widely used approach in the recognition of acoustic signals. There are ergodic hidden markov models or models in which each state of the model can be obtained from any other state in a finite number of steps, autoregressive hidden markov models, hidden markov models with continuous observation density, hidden markov models with zero transitions and coupled states, hidden markov models with an explicitly specified state duration density function. The most suitable model architecture for determining the operational condition of tires is the left-right or Backis model. This model is with a finite number of states. Each state S_t changes once at each time t. Observations O_t determines from the calculation of the probability distribution density of the occurrence of observation symbols in state j, $B = b_j(O_t)$. Moreover, transitions from state i to state j are also probabilistic and are determined by the discrete probability of transitions between states by the matrix of transition probabilities) $A = |a_{ij}|$.

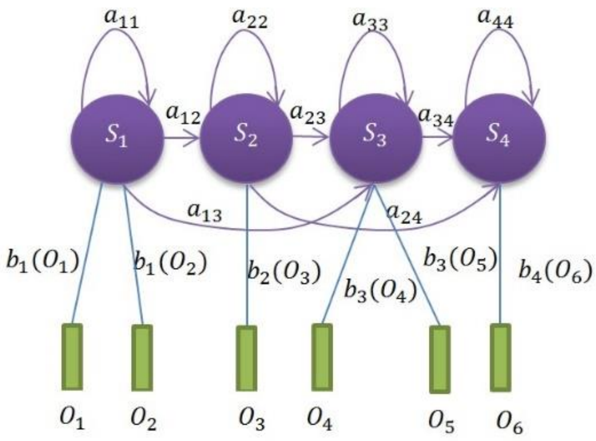

Fig. 2. Left-right hidden Markov model.

On Fig. 2 shows an example of a hidden Markov process in which the four model states pass from left to right $X = 1, 1, 2, 2, 3, 3, 4$ in the order corresponding to the sequence of observations from O_1 to O_6.

To simulate signals whose properties change over time, a left-right hidden Markov model is used, since transitions to states whose index is less than the index of the current state are not allowed, the main property of all left-right hidden Markov models is expressed through the values of transition probabilities:

$$a_{ij} = 0, j < i$$

Since the sequence of states must start at state 1 (and end at state N), the initial distribution of states has the properties:

$$\pi_{\mathrm{i}} = \begin{cases} 0, i \neq 1 \\ 1, i = 1 \end{cases}$$

In order to avoid serious jumps in the state indices when using left-right models, additional restrictions are imposed on the transition probabilities. Such as type constraints:

$$a_{ij} = 0, j > i + \Delta$$

In particular, for the model shown in Fig. 2, the value of Δ is 2, that is, transitions through more than one state are not allowed.

The matrix of transition probabilities of the hidden part of the model (Fig. 2) has the form:

$$A = \begin{bmatrix} a_{11}\ a_{12}\ a_{13}\ 0 \\ 0\ a_{22}\ a_{23}\ \ a_{24} \\ 0\ 0\ a_{33}\ \ a_{34} \\ 0\ 0\ 0\ a_{44} \end{bmatrix}$$

From this it is obvious that the transition probabilities for the last state of the left-right model are defined as follows:

$$a_{NN} = 1, a_{Ni} = 0, i < N$$

Since any parameters of the hidden Markov model, initially equal to zero, will retain their zero values even when using the procedure for reestimating model parameters, then imposing restrictions corresponding to the left-right hidden Markov model or models with limited transitions, in fact, does not affect this model in any way. procedure.

There are three main problems associated with the use of a hidden Markov model.

The first problem is reduced to estimating the probability $P(O/\lambda)$ of the occurrence of a sequence of observations $O = O_1, O_2, \dots, O_t$ (in this case, vectors of audio signal features) for $\lambda = (A, B, \pi)$. The forward-reverse algorithm is used to estimate the likelihood.

The second task is signal recognition. Let a sequence of observations $O = O_1, O_2, \dots, O_t$ and a hidden Markov model – λ be given. How to choose a sequence of states $Q = q_1 q_2 \dots q_t$, which will be optimal in some significant sense (for example, best fits the existing sequence of observations). The Viterbi algorithm is used to solve this problem.

The third task is training a hidden Markov model. How should the model parameters $\lambda = (A, B, \pi)$ be adjusted in order to maximize $P(O/\lambda)$. This problem is solved using iterative learning algorithms using the Baum–Welch method, the EM method, or using gradient methods.

Other methods include Support Vector Machines, wavelet analysis, but these algorithms have not found widespread use in acoustic signal recognition systems.

For our purposes, the most promising approach is to build a mathematical model based on a hidden Markov model due to the fact that this class of stochastic models showed the best results in recognizing complex acoustic signals, including continuous speech. In addition to the possibility of sound recognition, the hidden Markov model makes it possible to improve the quality of a signal polluted by noise and distortion, and to synthesize a signal. In addition, this approach shows the highest recognition accuracy.

Conclusions

1. The key point in creating a system for determining the technical condition of an object by sound is the qualitative cleaning of the acoustic signal from noise and the subsequent analysis of the spectral characteristics. The most promising approach for cleaning signals is adaptive filtering, since adaptive filters allow you to work with a signal in which noise characteristics are constantly changing and cannot be predicted. The adaptive filter is adjustable and automatically adjusts to the noise impulse response to minimize filtering errors. In the subsequent analysis, two approaches, wavelet analysis and spectral analysis, can be used. Wavelet analysis is suitable for an in-depth study of the spectral characteristics of a signal, but to create a universal method for processing audio signals to simulate the state of various technical objects, it is more appropriate to use Fourier analysis.

2. The most promising artificial intelligence methods for automatic recognition of acoustic signals are neural networks, hidden Markov models and dynamic programming methods. When building a system for determining the state of a technical object by sound, it is advisable to use an approach based on hidden Markov models, since this method improves the quality of a signal contaminated with noise and distortion, and also shows the highest recognition accuracy.

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СКРЫТЫЕ МАРКОВСКИЕ МОДЕЛИ ТЕХНИЧЕСКОГО КОНТРОЛЯ ПАРАМЕТРОВ ТЕХНИЧЕСКОГО СОСТОЯНИЯ САМОХОДНЫХ ОПРЫСКИВАТЕЛЕЙ

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Аннотация. Основным показателем, используемым при исследовании надежности являются скрытые марковские опрыскиватели, под которым понимается вероятность того, что самоходный опрыскиватель окажется в работоспособном состоянии в произвольный момент времени, кроме запланированных периодов, в течение которых применение самоходных опрыскивателей по назначению не предполагается. Вывод аналитического выражения для скрытых марковских моделей технического контроля параметров технического состояния самоходных опрыскивателей – довольно трудоемкая операция. Трудоемкость растет с усложнением графа, то есть при стремлении учесть больше технических состояний, факторов, влияющих на процесс технического контроля самоходных опрыскивателей. В этой связи решение задачи такого плана целесообразно проводить с помощью имитационной модели. С помощью инструмента моделирования Stateflow программного пакета Matlab разработана модель, позволяющая моделировать дискретно-событийные модели. Модель самоходных опрыскивателей среди Stateflow для оценки коэффициента готовности при проведении технического контроля над программами. Результатами имитационного моделирования являются значения скрытых марковских моделей технического контроля параметров технического состояния самоходных опрыскивателей при различных программах технического контроля, что позволяет сделать выводы о влиянии программы технического контроля самоходных опрыскивателей на значение коэффициента готовности.Вероятности ошибок при этом варьировались в пределах от 0 до 1, что вполне обосновано в случаях, когда технический контроль отличается только местом измерения параметра технического состояния, а средства измерения одинаковы. Автором установлено, что коэффициент готовности чувствителен к ошибке второго рода в данном случае. Пути дальнейших исследований встречаются в исследовании других программ технического контроля самоходных опрыскивателей, в которых коэффициент готовности чувствителен к вероятности ошибок первого рода.

Ключевые слова: имитационная модель, коэффициент готовности, самоходный опрыскиватель, технический контроль.

СКРИТІ МАРКІВСЬКІ МОДЕЛІ ТЕХНІЧНОГО КОНТРОЛЮ ПАРАМЕТРІВ ТЕХНІЧНОГО СТАНУ САМОХІДНИХ ОБПРИСКУВАЧІВ

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Анотація. Основним показником, що використовується для дослідження надійності є скрытые марковские модели технического контроля параметров технического состояния самоходных опрыскивателей, під яким розуміється ймовірність того, що самохідний обприскувач опиниться у працездатному стані у довільний момент часу, крім запланованих періодів, протягом яких застосування самохідних обприскувачів за призначенням не передбачається. Виведення аналітичного виразу для скрытых марковских моделей технического контроля параметров технического состояния самоходных опрыскивателей – досить трудомістка операція. Трудомісткість зростає з ускладненням графа, тобто при прагненні врахувати більше технічних станів, чинників, які впливають процес технічного контролю самохідних обприскувачів. У зв’язку з цим розв’язання задачі такого плану доцільно проводити за допомогою імітаційної моделі. За допомогою інструменту моделювання Stateflow програмного пакету Matlab розроблено модель, яка дозволяє моделювати дискретно-подійні моделі. Модель самохідних обприскувачів серед Stateflow для оцінювання коефіцієнта готовності під час проведення технічного контролю за програмами. Результатами імітаційного моделювання є значення скрытых марковских моделей технического контроля параметров технического состояния самоходных опрыскивателей при різних програмах технічного контроля, що дозволяє зробити висновки про вплив програми технічного контролю самохідних обприскувачів на значення коефіцієнта готовності. Імовірності помилок при цьому варіювалися в межах від 0 до 1, що цілком обґрунтовано у випадках, коли технічний контроль відрізняється лише місцем вимірювання параметру технічного стану, а засоби вимірювання при цьому однакові. Авторкою встановлено, що коефіцієнт готовності чутливий до помилки другого роду в даному випадку. Шляхи подальших досліджень зустрічаються у дослідженні інших програм технічного контролю самохідних обприскувачів, у яких коефіцієнт готовності чутливий до ймовірності помилок першого роду.

Ключові слова: імітаційна модель, коефіцієнт готовності, самохідний обприскувач, технічний контроль.

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