Application of Innovative Approaches to Video Segmentation in a Criminal Process

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Abstract

Video data segmentation, processing, analysis and indexing of segmentation results in time and space are proposed to improve the efficiency of systems for metric search and recognition of dynamic visual information in databases with a query `ad exemplum`; declared the possibility and usefulness of using video segmentation, based on the analysis of multidimensional time series, in the criminal process, emanated on the need to introduce innovative technologies into the criminal process.

Keywords[1]

Video surveillance, criminal procedure, innovative technologies in criminal procedure, video segmentation, video data search.

1. Introduction. Formulation Problem in General

Protection of a person, society and the state from criminal offenses, protection of the rights, freedoms and legitimate interests of participants in criminal proceedings, as well as ensuring a prompt, complete and impartial investigation and judicial investigation so that everyone who committed a criminal offense is brought to justice in moderation of his guilt, not a single innocent person was accused or convicted, not a single person was surrendered to unreasonable procedural compulsion and that due process is applied to each participant in criminal proceedings, is the task of the criminal procedure [1].

Video surveillance in public places is becoming more widespread. The rapid development of technology and the growing sense of insecurity among the population has gradually led the population to perceive video surveillance as a useful tool in the context of crime prevention and detection [2].
Indeed, the use of video surveillance allows you to record the events taking place objectively, unlike a person, whose perception of information is subjective. The law [1] defines evidence in criminal proceedings as factual data obtained in the manner prescribed by it, on the basis of which the investigator, prosecutor, investigating judge and the court establish the presence or absence of facts and circumstances relevant to criminal proceedings and are subject to proof. Among the procedural sources of evidence, the Law also names documents - material objects specially created for the purpose of preserving information, containing information recorded with the help of, including images, information that can be used as evidence of a fact or circumstances established during criminal proceedings. Such documents may include video recording materials, including electronic ones.

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Currently, the law enforcement system of Ukraine is undergoing reforms that are impossible without considering the use of modern information technologies. The use of video surveillance in law enforcement can increase the efficiency of public order protection and public safety [3].

Object detection is a key module in most visual filming, video surveillance and security applications.

The intensive development and widespread dissemination of information and communication technologies in the modern world aggravated by the complication of social relations in the direction of political and economic unification and diversification determine the modernization of society, which is manifested in the digitalization of social relations and management processes, as well as in the creation of a single information space on the basis of the Internet network [4].

In navigation and tracking systems, the proposed approaches for analysing video sequences can be used to obtain data on scene changes, in particular, this concerns issues of video surveillance over a certain area. The approaches, proposed in this work, make it possible to record and save only that information that is "essential", i.e. the one that occurs in the event of a significant change in the video data. Thus, it is supposed to increase the efficiency of search and recognition of visual information necessary for solving tasks of criminal proceedings.

2. Related Works

Valid search for video data by meaningful criteria, in particular, with 'ad exemplum' queries, is provided by the development of methods and models for indexing video data, the synthesis of measures and metrics for comparing events, plots, scenarios, the implementation of relevant feedback in order to iteratively clarify the information needs of the User.

Interdisciplinary multifactorial integration of methods of pattern recognition, computer vision, database management, analysis of multidimensional time series, artificial intelligence in general is the way to create such systems. The main influence on the development of methods for processing visual information that determine the tools of such systems was exerted by Ukrainian and foreign scientists S.G. Antoshchuk, A.M. Akhmetshin, E.V. Bodyansky, H. Burkhardt, R.M. Haralick, Z. Hu, G. Liu, , V.P. Mashtalir, S. V. Mashtalir V.N. Krylov, D.D. Pieleshko, E.P. Putyatin, M.I.Shlesinger, T.E. Rak, M. Sonka, R.A. Vorobel, P. Zezula, G.N. Zholtkevich and others.

Analysis of the state and trends in the development of methods for searching for visual information with query `ad exemplum` allows us to assert that, despite numerous studies in this direction, the growth of the accumulated video data and the intensification of their use require the creation of new high-speed valid search tools.

A certain perspective is the carrying out of theoretical and experimental studies on the development of models and methods for ensuring increased performance of metric search based on two-stage video segmentation: in time to obtain homogeneous (in a broad sense) video segments and in space (in the field of view) to obtain multidimensional time series, analysis which creates the prerequisites for video indexing.

Thus, the study of the approaches of segmentation of multidimensional time series induced by the segmentation of individual video frames, as well as the identification of necessary and sufficient conditions that can significantly speed up the search, is an urgent task.

We believe that the prospect of using innovative approaches in criminal proceedings proposed by the authors deserves the interest of appropriate proficient for further studies.

3. Methods

The research used the basic provisions of the mathematical apparatus for pattern recognition, artificial neural networks (ANN), set theory, algebra, elements of mathematical statistics.

4. Formulation of Goals

The purpose of the study was to develop approaches for video data segmentation, processing, analysis and indexing of segmentation results in time and space to improve the efficiency of metric search and recognition systems for dynamic visual information in databases with queries based on the pattern, and writing an article is an attempt to declare the possibility and usefulness the use of video segmentation based on the analysis of multidimensional time series in the criminal process, based on the need to introduce innovative technologies into the criminal process.

5. Main Part

5.1. Detecting property changes in multidimensional time series based on custom model

Let us assume that in some feature space there are a multidimensional time series [5], that characterize the video $x(k) = (x(k), x(k),..., x(k))^T$, where $1 \leq k \leq N-$ is discrete time, at moments which observations are made. The segment of this series $S(a, b) = \{a \leq k \leq b\}$ is a statistically homogeneous sequence $x(a), x(a+1), ..., x(b)$, and the problem of time segmentation is a search c disjoint segments $S^C=\{S_i(a, b), 1 \leq I \leq c\}$, such that что $a_1 = 1, b_c = N, a_i = b_{i-1} + 1$. So, it is necessary to find c intervals $S_1 < Sa < ... < Sc$ and their boundaries a_i, b_i.

Consider a sequential, on-line implementation-oriented detection of changes in the properties of multidimensional time series in the process of adaptive identification of the VAR process model, which in the general case connects past and current observations $x(k)$ in the form:

$$x(k) = B_0 + \sum_{i=0}^{n} B_l\, x(k-l) + \xi(k) \quad (1)$$

where $B_0=\{b_{0i}\}-(n\times 1)$ - vector of mean values,

$B_l = \{b_{lij}\}-(n\times n)$ - parameter matrices,

$p-$ model order.

It should be emphasized that the initial information for solving the problem of identification and detection of changes is only the n-dimensional time series $x(k)$ itself, the values of which arrive sequentially in time.

To simplify further calculations, we introduce into consideration the composite ones: matrix $B = (B_0 \vdots B_1 \vdots \ldots \vdots B_p)$ and vector $X(k)=(1,x^T(k-1),..., x^T(k-p))^T$ dimensions $(n\times(pn+1))$ and $((pn+1)\times 1)$ respectively, after which we rewrite equation (1) in the form

$$x(k) = BX(k) + \xi(k), \quad (2)$$

where the matrix of a priori unknown parameters B contains practically all the necessary information about the properties of the controlled signal.

The identification problem is that in accordance with the real signal (2) a tunable model

$$\hat{x}(k) = B(k-1)\, X(k), \quad (3)$$

the matrix of parameters $B(k)$ of which is refined at each time step k by minimizing the accepted identification criterion, which is a certain function of the difference between the calculated $\hat{x}(k)$ and experimental data $x(k)$. So, the synthesized model (3) must be workable in the forecasting mode, and the violation of predictive properties can be a sign of the occurrence of certain recurrent procedures, which can be presented in a generalized form [6]:

$$\begin{cases} B(k) = B(k-1) + \gamma(k) e X^T(k); \\ e(k) = x(k) - \hat{x}(k) - B(k-1)X \end{cases} \quad (4)$$

where $\gamma(k)$ is the scalar or matrix gain of the algorithm, which determines its properties and depends on the adopted identification criterion; $e(k)$ - vector identification error.

In practice, the most widespread algorithms are those associated with the criterion for the minimum sum of squares of identification errors

$$I(k) = \sum_{u=1}^{k} \beta(u) \parallel e(u) \parallel^2 = \sum_{u=0}^{k} \sum_{i=1}^{n} \beta(u) e_b(u)^2 \quad (5)$$

and its modifications determined by the adopted system of weights β(u). The well-known is the least squares method, in which all weights have the same weight, that's

$$I(k)=\sum_{u=1}^{k}\parallel e(u)\parallel^2. \quad (6)$$

The algorithm corresponding to (4), (6) has the form:

$$\begin{cases} B(k)=B(k-1)+\frac{e(k)X^T(k)P(k-1)}{1+X^T(k)P(k-1)X(k)}; \\ P(k)=P(k-1)-\frac{P(k-1)X(k)X^T(k)P(k-1)}{1+X^T(k)P(k-1)X(k)} \end{cases} \quad (7)$$

and with constant parameters (2) provides monotonic convergence of estimates $B(k)$ to the true values of parameters B. We assume that the recursive least squares method is not suitable for detecting changes in properties. The choice to (6), (7) is the one-step procedure

$$B(k)=B(k-1)+\frac{e(k)X^T(k)}{X^T(k)X(k)}, \quad (8)$$

generated by the one-step identification criterion

$$I(k)=||e(k)||^2 \quad (9)$$

and is a generalization of the Kachmazh algorithm [7] to the vector-matrix model (3). Having a high speed, procedure (8) does not have filtering properties, and therefore is not able to distinguish between changes in the signal and the influence of the stochastic component $\xi(k)$.

In this regard, it seems expedient to use finite memory algorithms that have both smoothing and tracking properties, the compromise between which is set by the size of the memory. Loss of predictive properties of the model (3) and the need to rebuild the memory of the algorithm can serve as a sign of emerging changes.

Returning to criterion (5), we note that in the class of algorithms generated by it, the exponentially weighted least squares method with the criterion

$$I(k)=\sum_{u=1}^{k}\beta^{k-u}\parallel e(u)\parallel^2 \quad (10)$$

and a recurrent setup procedure

$$\begin{cases} B(k)=B(k-1)+\frac{e(k)X^T(k)P(k-1)}{\beta+X^T(k)P(k-1)X(k)}; \\ P(k)=\frac{1}{\beta}(P(k-1)-\frac{P(k-1)X(k)X^T(k)P(k-1)}{\beta+X^T(k)P(k-1)X(k)}, \end{cases} \quad (11)$$

where $0<\beta\leq 1$ is the smoothing parameter.

At this point, it should be noted that an identifier with exponential smoothing is generally unstable, which leads to an "explosion of parameters" of the covariance matrix, which occurs especially often at high dimensions of the processed signal $x(k)$. Thus, using the traditional exponentially weighted recurrent least squares method is complicated by the poor conditioning of the information matrix

$$\sum_{u=1}^{k}\beta^{k-u}X(u)X^T(u), \quad (12)$$

generated by a high level of correlation between the components $x_i(k)$.

Replacing the operation of inversion of the weighted information matrix (based on the Sherman-Morrison formula) with the operation of pseudo-enrichment using Greville's theorem solves the problem [8]. However, the new algorithm is too cumbrous from a computational point of view, especially for large n.

As a result of that, should pay attention to the use of a multidimensional modification of the exponentially weighted stochastic approximation algorithm [9] in the form:

$$\begin{cases} B(k)=B(k-1)\frac{e(k)X^T(k)}{\beta r(k-1)+\parallel X(k)\parallel^2}; \\ r(k)=\beta r(k-1)+\parallel X(k)\parallel^2, \end{cases} \quad (13)$$

which is a kind of compromise between procedures (8) and (11) and has the necessary smoothing and tracking properties.

In [10, 11], a method for regulating the smoothing parameter b is proposed, based on the control of statistics characterizing the prediction error of a one-dimensional signal. It is assumed that the tuning of the model parameters is performed using the exponentially weighted Kalman-Main algorithm, which for the *i-th* component $x_i(k)$ can be written as:

$$\begin{cases} b_i(k) = b_i(k-1) + \frac{(e(k)X^T(k)P_i(k-1))_i}{\beta\sigma_i^2 + X^T(k)P_i(k-1)X(k)}; \\ P_i(k) = \frac{1}{\beta}(P_i(k-1) - \frac{P_i(k-1)X(k)X^T(k)P_i(k-1)}{\beta\sigma_i^2 + X^T(k)P_i(k-1)X(k)}, \end{cases} \quad (14)$$

where $b_i(k)$ – i-th matrix row $B(k)$,

$(\mathrm{o})_i$– i-th the row of the corresponding matrix product.

If the variances of individual components $\xi_i(k)$ of the disturbance vector are unknown, then in (14) an estimate can be used in the form:

$$\begin{cases} \sigma_i^2(k) = \sigma_i^2(k-1) + P_i(k-1)\left(\sigma_i^2(k-1) - e_i^2(k)\right); \\ P_i(k) = \frac{1}{\beta}(P_i(k-1) - \frac{P_i^2(k-1)}{\beta + P_i(k-1)}, \end{cases} \quad (15)$$

It is also assumed that the model quite accurately describes the controlled signal at time intervals s of observations, and the parameters can change in jumps at arbitrary times k_a. The variable value $\beta(k)$ is regulated by statistics

$$T_i(k) = \sum_{u=k-s}^{k} \frac{e_i^2(u)}{\beta(k-1)\sigma_i^2 + X^T(u)P_i(u-1)X(u)}, \quad (16)$$

having x^2 distribution with s degrees of freedom, while $\beta(0)=1$. Regulation $\beta(k)$ is performed at discrete times ts according to the following rule:

$$\beta(k) = \begin{cases} 1 \; at \; k < s, \; k = ts \; and \; T_i(k) \le x_j^2; \\ \beta(k-1) - \Delta\beta \; at \; k = ts \; and \; T_i(k) > x_j^2; \\ \beta(k-1) \; at \; ts < k < (t-1)s, \; t = 1, 2, \ldots \end{cases} \quad (17)$$

Here x_j^2 is the quantile of the law x^2, corresponding to the significance level j, $\Delta\beta$ is the regulation step.

Rule (17) provides for a change in $\beta(k)$ for values of k, that are multiples of s (for intermediate k, the value of $\beta(k)$ remains unchanged), the fact of changes is recorded at the moment the second relation (17) is realized.

The cumbersomeness and inertia of this procedure forces us to look for other faster and more effective methods of detecting changes. So, in [12], a method for regulating the smoothing parameter b based on the Mann-Whitney criterion was proposed. In this case, the controlled characteristic is the value

$$\sum_{u=k-s+1}^{k} sign(x_i(u) - \hat{x}_i(u)) \ge \gamma, \quad (18)$$

where γ – some threshold value,

s - the size of the sliding control window,

$$sign(x_i(u) - \hat{x}_i(u)) = \begin{cases} 0 \; at \; x_i(u) = \hat{x}_i(u); \\ +1 \; at \; x_i(u) > \hat{x}_i(u); \\ -1 \; at \; x_i(u) \le \hat{x}_i(u). \end{cases} \quad (19)$$

The control process begins with the value $\beta(1)=0$, which corresponds to the maximum speed of algorithm (13). The exponentially weighted recursive least squares method in this situation, of course, is fundamentally inoperable. During the authentication may arise:

$$\sum_{u=k-s+1}^{k} sign(x_i(u) - \hat{x}_i(u)) < \delta, \quad (20)$$

which means the dominance of the stochastic component ξ_i of the signal x_i over the "drift" one. In this case, it is necessary to improve the smoothing properties of the algorithm, i.e. increase it according to the rule: $\beta(k) = \beta(k-1) + \Delta\beta$.

In situation (18), the drift component of the signal prevails and the algorithm does not have time to track the changes that have arisen. In other words, it is worth to decrease storage $\beta(k) = \beta(k-1)$ - $\Delta\beta$ and record the fact of changes.

To control changes in a multidimensional time series, it is proposed to use a modification (18) in the form:

$$max_i \left(\sum_{u=k-s+1}^{k} sign(x_i(u) - \hat{x}_i(u))\right) \ge \gamma, \quad (21)$$

Actually, not statistical, but heuristic procedures e. g. the methods of Chow, Brown, Trigga-Leach, Shawn, etc. have become more widespread [12, 13, 14, 15], based on some heuristics, and therefore bearing an element of subjectivity. Given the shortage of a priori and current information on the characteristics and properties of the monitored signal, preference should naturally be given to these methods. The basis of most heuristic methods is as follows: a set of values for the smoothing parameter β, is specified, for example, 0; 0.05; 0.1; ... 0.95; 1 and a set of characteristics that determine the quality of identification. Most often these are:

- is the current estimation error of the i-th component: $e_i(k, β) = x_i(k) - \hat{x}_i(k, β)$;
- the cumulative sum of errors: $G_i(k, β) = e_i(k, β) + G_i(k-1, β)$;
- mean absolute error: $d_i(k, β) = (1-β) e_i(k, β) + β d_i(k-1, β)$;
- average error: $\bar{e}_i(k,\beta) - (1-\beta)e_i(k,\beta) + \beta\bar{e}_i(k-1,\beta)$;
- relative mean error: $\tilde{e}_i(k,\beta) = (1-\beta)\frac{e_i(k,\beta)}{x_i(k)} + \beta\tilde{e}_i(k-1,\beta)$;
- root mean square error: $\bar{e}_i^2(k,\beta) = (1-\beta)\bar{e}_i^2(k,\beta) + \beta\bar{e}_i^2(k-1,\beta)$.

The smoothing parameter β should be adjusted accordingly. The adoption of such a decision is associated with changes, that have occurred as a result of exceeding a certain threshold γ value of the selected controlled characteristic.

A stationary stochastic signal is usually associated with a value of β lying in the interval $0{,}7 \le \beta \le 0{,}9$ [15]. The simplest form of control is that when the value of $\tilde{e}_i(k, \beta)$ for some β exceeds the threshold 0.05 [13], the smoothing parameter decreases according to the rule: $\beta(k) = \beta(k-1) - \Delta\beta$, and the identification process continues with a new $\beta(k)$. If the value of β exceeds the threshold of $0{,}7 \le \beta(k) \le 0{,}7)$, a decision is made on the occurrence of a change in the signal.

The Chow method adjusts three models simultaneously with the values of the smoothing parameters β, $\beta+\Delta\beta$ and $\beta-\Delta\beta$. It seemed to be more effective, albeit more complicated.

The Chow method is more effective, but also more complex. Here, three models with the values of the smoothing parameters β, $\beta+\Delta\beta$ and $\beta-\Delta\beta$ are simultaneously adjusted. For example, the best result is obtained, when the current time k from $\beta(k)=\beta+\Delta\beta$, then on the next time step, a new triple of smoothing parameters β, $\beta+\Delta\beta$ and $\beta+2\Delta\beta$ is used. In the case, when the best model is achieved at $\beta(k)=\beta-\Delta\beta$, after a triple β, $\beta-\Delta\beta$, $\beta-2\Delta\beta$ are formed, finally, in the case, when the best result is obtained at $\beta(k)=\beta$, the set β, $\beta+\Delta\beta$, $\beta-\Delta\beta$ are preserved.

Simpler and more efficient methods are those using a tracking signal, which is an indicator of changes in monitored signals [14, 15]. There are a number of forms of the tracking signal, while its going beyond certain limits indicates changes that have occurred.

R. Brown proposed to use the expression [16] as a tracking signal:

$$T_i^B(k) = \frac{\sum_{u=1}^{k} e_i(u)}{\sqrt{\sigma_i^2(k)}} \tag{22}$$

the physical meaning of which is that if the tuned model is adequate to the controlled signal, the sum of errors varies around 0, while not exceeding some boundaries that are set a priori for a given level of probability for a certain variance of the sum of forecast errors, which tends to the value

$$\lim_{k\to\infty} \sigma_i^2(k) = \frac{1}{1-(1-\beta)^{2(pn+1)}}\sigma_i^2. \tag{23}$$

D. Trigg, A. Leach suggested using the ratio [17]:

$$T_i^{TL}(k)\frac{T_i^{`}(k)}{d_i(k)}, \tag{24}$$

where $T_i^{`}(k) = (1-\beta)e_i(k) + \beta^{`}T_i^{`}(k-1)$

In other words, this is not the total amount of deviations, but a smoothed error, and the inequality must be follow $\beta' \le \beta$.

At $\beta'=\beta$ the tracking tone will vary between –1 and +1. To introduce automatic feedback, D. Trigg, A. Leach suggested to computating the smoothing parameter therefore the relation $\beta(k) = 1 - |T^{TL}(k)|$

and fix the discrepancies in the signal with significant changes in $\beta(k)$.

Mention should be made of Shaun's modification [15]: $\beta(k) = 1 - |T^{TL}(k-1)|$.

A growing of the tracking signal indicates an increase in the discrepancy among the model and the controlled sequence, to compensate for which, a faster response of the identifier is required, which is provided by a lower value of the smoothing parameter. This provides negative feedback.

In [13] it is emphasized that in identifying processes with a sufficiently smooth drift, Brown's method has advantages. Sharp spikes are better identified with the Trigga-Leech tracking signal. Just like that this form maybe useful when analysing changes in a time series.

5.2. Detect property changes in multivariate time series based on exponential smoothing

The main disadvantage of the approach to detecting changes considered above is a significant number of parameters of the tunable model (3), which is $n(pn+1)$, which can cause certain difficulties at large n and high frequencies of information arrival for processing. A fairly convenient mathematical tool for solving the problem of detecting changes in the properties of one-dimensional stochastic sequences is exponential smoothing [14, 15, 16], the essence of which can be illustrated by the following example.

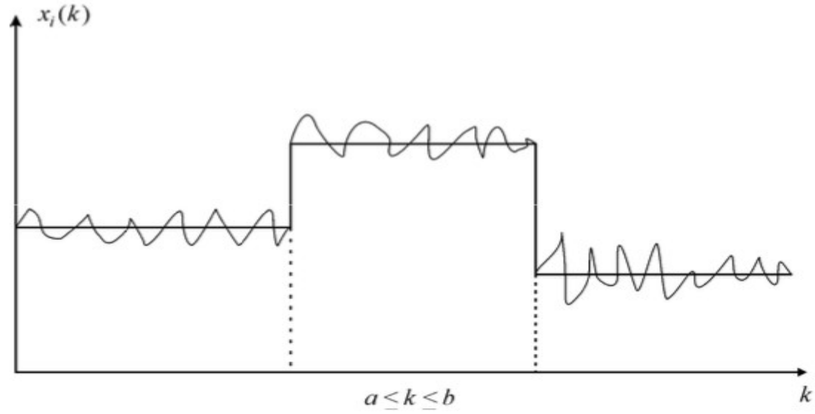

Figure 1: Discontinuous changes in the mean level of the time series [18]

Let us introduce an elementary model of the form:

$$x_i(k) = b_i + \xi_i(k) \quad (25)$$

and suppose that the coefficient b_i can change abruptly from time to time as shown in Figure 1.

Worth mentioning about the magnitude and time of change of the coefficient b_i are a priori unknown, and the time interval b-a, during which the value of the coefficient b_i remains unchanged, significantly exceeds the signal quantization step (the time between two consecutive observations).

Since exponential smoothing is designed to solve the forecasting problem, we first consider the problem of constructing a forecast $\hat{x}_i(k+1)$ at time k. Let us also assume that the parameters of model (25) at the moment $k+1$ coincide with those that we received by the moment k. In this case, the problem is reduced to estimating the current value $b_i(k)$ from k previous observations. Since the value of b_i changes over time, then to obtain this estimate, observations $x_i(k), x_i(k$-$1),...$ should be taken with a greater weight than observations obtained much earlier. In principle, this problem can be successfully solved using the simplest sliding window method; moreover, if the size of this window s is given, then the smoothed estimate has the form:

$$\bar{x}_i(k) = \frac{1}{s}\sum_{u=k-s+1}^{k} x_i(u). \quad (26)$$

The reaction rate of an identifier using a sliding window apparatus to a change in the signal depends on the value s of the averaged recent observations. This speed increases with decreasing s and vice versa. On the other hand, a decrease in s in the absence of data changes decreases the accuracy of the resulting estimate $b_i(k) = \bar{x}_i(k)$, since its variance can be written as:

$$\sigma_{bi}^2 = \frac{\sigma_i^2}{s}. \quad (27)$$

This shows that the accuracy of the $b_i(k)$ estimate and the response rate of the identifier are contradictory requirements. Taking into account the obvious relation

$$\bar{x}_i(k) = \bar{x}_i(k-1) + \frac{x_i(k) - x_i(k-s)}{s},$$

or

$$s_i(k) = \alpha x_i(k) + (1-\alpha)s_i(k-1) = \alpha x_i(k) + \beta s_i(k-1), \quad (28)$$

where procedure (28) is the traditional exponential smoothing.

In expression (28), to distinguish exponential smoothing from the moving average, the notation $s_i(k)$ is introduced instead of $\bar{x}_i(k)$. The quantity α, which is analogous $1/_S$ to the moving average, determines the weights of the observations present in the smoothed estimate.

From expression (28) it follows that the current value of the smoothed value $s_i(k)$ is equal to its previous value plus some fraction of the difference between the current observation and the previous value of the smoothed value. Since operation (26) is implemented for all observations of the time series, it can be rewritten considering all previous observations in the form: $s_i(k) = \alpha x_i(k) + (1-\alpha)(\alpha x_i(k-1) + (1-\alpha)s_i(k-2)) = x_i(k) + (1-\alpha)(\alpha x_i(k-1) + (1-\alpha)(\alpha x_i(k-2) + (1-\alpha)s_i(k-3))) = \cdots = \alpha\sum_{u=0}^{k-1}(1-\alpha)^u x_i(k-u) + (1-\alpha)^k x_i(0)$.

Thus, the value $s_i(k)$ is a certain combination of all previous observations, the weight of which decreases exponentially with time. The current observation has weight α, the value of which lies in the interval [0,1]. The limiting value α=0 corresponds to the case $s = \infty$ in the moving average. Moreover, $s_i(k) = s_i(k-1)$, that is, the s_i value is independent of new information. The limit value α=1 means that the background does not affect the current rating at all, i.e. $s_i(k) = x_i(k), and \sigma_{bi}^2 = \sigma_i^2$.

Thus, the accuracy and speed of the response of the identifier to the rate of change in the signal completely depends on the accepted value α. A small value of provides a greater accuracy in estimating b_i at a stationary signal, but a slow response to changes, while an increase α in will increase the rate of this reaction.

Usually [16], the value of a is in the range from 0.01 to 0.3, and the number *s* is in the range from 6 to 200. Since this range is large enough, in each specific problem this parameter must be selected in a special way. The need to use large values of α (small values of *s)* indicates a discrepancy between the selected and real models of the monitored signal, i.e. can serve as a sign of a change in its properties.

It was noted above that with exponential smoothing, the weight of the current observation has a value of α, and the weights of the previous observations decrease in reverse time. In moving average, the average weight of the last *s* observations is assumed to be the same and equal $1/_S$. The weights of all early observations are equal to 0.

In [14], the concept of average "age" in moving average was introduced in the form:

$$p = \frac{1}{s}(0 + 1 + 2 + \cdots + k - 1) = \frac{s(s-1)}{2s} = \frac{1}{2}(s-1). \quad (29)$$

As follows from (29), the average "age" of observations is the average of the "ages" of all individual observations, taken with weights equal to the weights of these individual observations. With exponential smoothing, the weight of an observation made at time *k-l,* will be $\alpha\beta^l$, so the average "age" of observations can be written as: $p = 0\alpha\beta^0 + 1\alpha\beta^1 + \cdots + l\alpha\beta^1 + \cdots = \alpha\sum_{u=0}^{\infty} u\beta^l$.

The condition of equality of the average "age" of observations in the moving average and with exponential smoothing allows finding the relationship between the parameter α and the window *s* in the form:

$$\frac{\beta}{\alpha} = \frac{1-\alpha}{\alpha} = \frac{s-1}{2} \quad \text{or} \quad \begin{cases} \alpha = \frac{s-1}{2} \\ \beta = \frac{s-1}{s+1} \end{cases} \quad (30)$$

Of interest to us is the response of an exponential smoothing identifier to jumps in the controlled signal. Let us assume that a unit jump occurs at time k_a, i.e. $b_i^a = b_i + 1$ for $k \geq k$. Using the standard discrete z-transformation [19], taking into account that $\xi[1] = \frac{z}{z-1}$, we can write:

$$\xi[b_i(k)] = \frac{\alpha z}{z-\beta^{To}} \cdot \frac{z}{z-1} \quad \text{or} \quad \frac{\alpha z}{z-\beta^{To}} \cdot \frac{z}{z-1} = \frac{\beta^{To}}{\beta^{To}-1} \cdot \frac{\alpha z}{z-\beta^{To}} + \frac{\alpha}{1-\beta^{To}} \cdot \frac{z}{z-1}, \tag{31}$$

where T_0 – monitored signal quantization period.

Going back to the time domain, we get

$$\beta_i(k) = 1\frac{\alpha}{1-\beta^{To}} - \alpha\frac{\beta^{To}}{1-\beta^{To}}\beta^k, \tag{32}$$

whence it follows that an identifier with exponential smoothing comes to a new steady state $b_i + 1$ or faster than less β (more α).

The general procedure for exponential smoothing (28) is intended for processing one-dimensional signals $x_i(k)$. Within the framework of the problem we are considering, it is advisable to introduce exponential smoothing of multidimensional sequences in the form:

$$s(k) = AX(k) + (I - A)s(k-1), \tag{33}$$

where $s(k) = (s_1(k), s_2(k), ..., s_n(k))^T$,

$A = diag\,(a_1, a_2, ..., a_n) – (n\,´\,n)$ - diagonal matrix,

$I – (n\,´\,n)$ - identity matrix.

If you use the Trigga-Licch tracking signal to control changes

$$\begin{cases} T_i^{TL}(k) = \frac{\grave{T}_i(k)}{d_i(k)}; \\ \grave{T}_i(k) = \grave{\alpha}_i e_i(k) + \grave{\beta}_i \grave{T}_i(k-1); \\ d_i(k) = \alpha_i|e_i(k)| + \beta_i d_i(k-1), \end{cases} \tag{34}$$

by analogy with (33), it is easy to introduce its vector analogue

$$\begin{cases} T^{TL}(k) = \frac{\grave{T}(k)}{d_i(k)}; \\ \grave{T}(k) = \grave{A} e_i(k) + (I - \grave{A})\grave{T}(k-1); \\ d_i(k) = diag\big(\alpha_i|e_i(k)| + (1-\alpha_i)d_i(k-1)\big), \end{cases} \tag{35}$$

in this case, naturally, each component of the $(n\text{x}1)$ -vector $T^{TL}(k)$ is controlled.

The occurrence of changes in the process is detected by testing for inequality $max_i(T^{TL}(k)T^{TL}(k-1)$ on type (21).

To control variances, we introduce a vector of squares of current $\Xi(k) = (e_1^2(k), e_2^2(k), ..., e_n^2(k))^T$ and an exponentially smoothed variance vector

$$S_{\sigma^2}(k) = A\Xi(k) + (I-A)S_{\sigma^2}(k-1) \tag{36}$$

It is clear that for a stationary signal and $\alpha_i = 1/k$ expression (36) describes the variances $\sigma^2 b_i$ of estimates of the components b_i, however, in a nonstationary situation at $0 \leq \alpha_i \leq 1$, the growth of the components of vector (36) indicates the occurrence of changes. Since in this situation the use of a tracking signal is impossible, it is necessary to control the condition

$$max_i(S_{\sigma^2}(k) - S_{\sigma^2}(k-1)) \geq \gamma_{\sigma^2} \tag{37}$$

Analysis of the internal structure of a stationary multidimensional time sequence can be carried out using its correlation matrix of the form:

$$R\,(k,\tau) = \frac{1}{k}\sum_{u=1}^{k}(x(u) - \bar{x})(x(u-\tau) - \bar{x})^T,\ \tau = 0, 1, 2, ..., \tau_{max}, \tag{38}$$

which contains information about the autocorrelation and cross-correlation functions of all components $x_i(k)$.

To detect changes in properties, you can enter an exponentially smoothed correlation matrix

$$S_R(k,t) = a(x(k) - S(k))(x(k-t) - S(k))^T, \tag{39}$$

control by means of inequality

$$S_p(S_R(k,\tau)\ S_R^T\ (k,\tau)) - S_p(S_R(k-1,\tau) S_R^T\ (k-1,\tau)) \geq \gamma_R, \quad (40)$$

where $Sp(\text{o})$ – matrix trace,

$S_p(S_R S_R^T)$ – square of the spherical norm of a matrix S_R.

Thus, based on the exponential smoothing methodology, it is possible to provide real-time control over the changes in all characteristics of multivariate time series.

5.3. Detecting property changes in multidimensional time series based on principal component analysis

An important problem in the analysis of large arrays (both in volume and in dimension) of observations given in the form of time series is the task of compressing them in order to isolate latent factors that determine the internal structure of the controlled signal, what in the end pursues the goal of making the initial time series simplier interpreted from the point of view of detecting property changes.

It is worth using a well-proven factor analysis apparatus for these purposes [20], which is characterized by using within which the method of principal components is most widely used (Karunen-Loev transformation).

The analysis starts with the $k \times n$ observation matrix

$$X = \begin{pmatrix} x_1(1) & x_2(1) & \cdots & x_n(1) \\ x_1(2) & x_2(2) & & x_n(2) \\ \vdots & & & \\ x_1(u) & x_2(u) & \cdots & x_n(u) \\ \vdots & & \ddots & \\ x_1(k) & x_2(k) & \cdots & x_n(k) \end{pmatrix}, \quad (41)$$

formed by an array of k n-dimensional observation vectors $x(u) = (x_1(u), x_2(u),\ldots, x_n(u))^T$, its correlation $(n \times n)$ matrix of the form

$$R(k) = \frac{1}{k}\sum_{u=1}^{k}(x(u)-\bar{x})(x(u)-\bar{x})^T = \frac{1}{k}\sum_{u=1}^{k} x^c(u)x^{cT}(u), \quad (42)$$

and $x^c(u)=x(u)-\bar{x}$ – mean-centered raw data.

The principal component method consists in projecting the observed input data from the initial n-dimensional space into the m-dimensional ($n>m\geq 1$) output space and reduces to finding a system $w^1, w^2, \ldots, w^m$ of orthogonal eigenvectors of the matrix $R(k)$ such that $w^1 = (w_1^1 w_2^1, \ldots, w_n^1)^T$ corresponds to the largest eigenvalue λ, of the matrix $R(k)$, $w^2 = (w_1^2 w_2^2, \ldots, w_n^2)^T$, the second largest eigenvalue λ and so on. Or the search for a solution to the matrix equation $(R(k)-\lambda_j I)w^j = 0$, such that $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n \geq 0$ и $||w^j||^2 = 1$.

If we use the terminology of algebra, the solution to this task is closely connected with the problem of finding the eigenvalues and rank correlation matrix. For geometry, the solution to this task provides for a transition to a space of a lower dimension with minimal information loss. Finding the set of orthonormal vectors in the input space that take on the maximum data variation is a task in the statistical sense. In turn meaning of algorithmic solution to this task consists in the sequential determination (selection) of a set of eigenvectors $w^1, w^2, \ldots, w^m$ by optimizing each of the local functional, forming a global test

$$I_w(k) = \frac{1}{k}\sum_{l=1}^{m}\sum_{u=1}^{k}(x^{cT}(u)w^l)^2 \quad (43)$$

with restrictions

$$\begin{cases} w^{lT}w^P = 0, at\ l \neq p; \\ \quad w^{lT}w^P = 1. \end{cases} \quad (44)$$

Maximization of the local criterion is the way by which can be found the first main component. This is what carries the maximum information about the monitored signal

$$I_w^l(k) = \frac{1}{k}\sum_{u=1}^{k}(x^c(u)w^1)^2 \quad (45)$$

applying Lagrange's standard method of indefinite factors [5].

The next step is to subtract from each vector its projection onto the first main component. component $x^c(u)$. Then the first main component of the residuals is calculated, which is simultaneously the second main component of the original data and is orthonormal to the first one.

After that, the third main component is calculated. Each source vector is projected onto the first and the second main components. This projection is subtracted from each $x^c(u)$ and the first main component of the resulting residuals is found, which is the third component of the original data. The rest of the main components are calculated recursively according to the proposed and described procedure.

It can be argued, that there is already a well-developed mathematical toolkit and software to implement the Karunen-Loev transformation. But it should also be noted their drawback, which concerns the need for a priori specification of the matrix X of a fixed dimension. But, when data is received sequentially in real time, standard factor analysis procedures become inoperable.

Taking into account the above, for finding the eigenvectors of matrix $R(k)$, it seems promising to use recurrent online procedures, with sequential processing of observations of a multidimensional time series $x(1), x(2), \ldots, x(k), x(k+1)\ldots$ and not to calculate the correlation matrix itself.

An artificial neuron based on an adaptive linear associator is described in [21] for calculating the first main component in real time. In Figure 2, a diagram of this neuron is produced, modified to solve the problem of detecting changes in properties in a multidimensional signal based on the analysis of the main component. The learning algorithm for pre-centered data can be written as

$$\begin{cases} w^l(k+1) = w^l(k) + \eta(k+1)\left(x(k+1) - y(k)w^l(k)\right)y(k+1), \\ \quad y(k+1) = x^T(k+1)w^l(k), w^l(0) \neq 0, y`(1) = x^T(1)w^l(0), \end{cases} \tag{46}$$

where $\eta(k+1)$ is a tuning step parameter chosen small enough to ensure stable operation of the algorithm [5].

Algorithm (46) provides the normalization of the vector $w^l(k)$: $\|w^l(k)\|^2 = 1$, the vector $w^1(k)$ itself is an eigenvector of the matrix $R(k)$. The maximum eigenvalue corresponds to it. The maximum possible dispersion is a characteristic of the output signal $y(k)$, which is explained by the content of the maximum information about the multidimensional input signal $x(k)$.

Then the output signal $x(k)$ is exponential smoothed, which filters out the noise components $\xi(k)$. Changes are detected using a one-dimensional tracking signal $T_i^{TL}(k)$ (24).

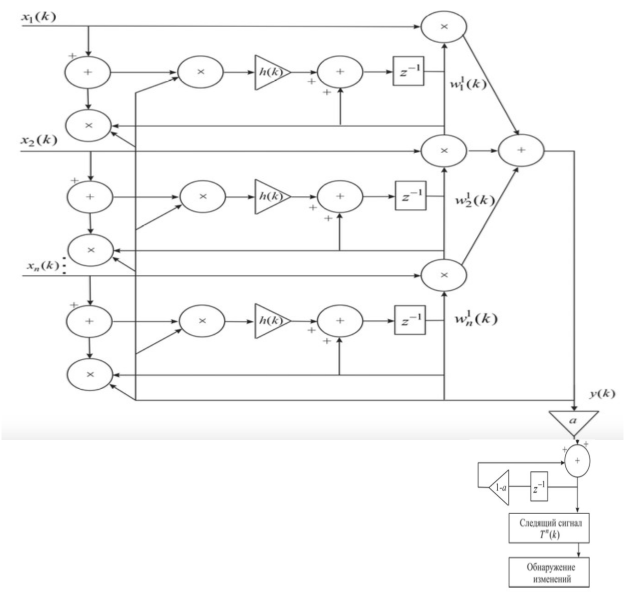

Figure 2: Modified neuron to detect changes in the properties of the main component of a multivariate time series [22]

5. Conclusions

The tasks of registration, accumulation, processing, analysis, storage, search, and interpretation of video streams are closely related to the analysis of time series, the main characteristic of which is significant uncertainty. Methods for identifying time series outliers are the basis for almost any video processing, search for homogeneous (in the broad sense, more precisely, in the sense defined by the subject area) sequences of images.

An effective alternative to statistical methods that require the restoration and estimation of the characteristics of the analysed data are adaptive procedures that allow solving problems of detecting possible changes in real time under conditions of a significant shortage of a priori information. In problems of video segmentation in the form of multidimensional non-stationary time series with a priori unknown characteristics, it seems most appropriate to use the adaptive approach.

Three approaches to detecting changes in the properties of multidimensional time series induced by video analysis in a certain feature space were considered.

Three approaches to detecting variations of properties of multidimensional time series, which were induced by video analysis in a certain feature space were considered.

The first of the considered approaches is based on the use of custom models and is the most reasonable from a mathematical point of view. However, to build an adequate mathematical model capable of effectively detecting the emerging disruptions, large training samples may be required, which is far from always possible, for example, with frequent changes in short-term plots.

The second approach is based on the use of multivariate exponential smoothing and is the simplest from a computational point of view. At the same time, for its work, it does not require significant number of information and allows you to effectively detect the emerging disruptions in the form of sharp jumps in feature descriptions. At the same time, it is characterized by some inertia, and this leads to a delay in the detection process, which, however, can be compensated for by using procedures for regulating the smoothing parameter using a tracking signal, but, unfortunately, this will complicate the computational model.

Finally, the third approach to detecting changes in the properties of multidimensional time series using principal component analysis (Karunen-Loev transformation) makes it possible to use the entire arsenal of existing methods for detecting mismatches of one-dimensional signals. However, its application is complicated by the fact that the algorithm for training the neuron-compressor is not an optimal procedure in terms of speed, which in some cases will lead to a "delay" in the learning process.

Thus, in conditions of a priori uncertainty (lack of completeness of description) when segmentation of video streams, it is advisable to use all the proposed approaches in parallel. The approaches of segmentation and video data processing proposed in the article can be introduced into the activities of law enforcement agencies, since create good prerequisites for improving the performance of various search engines, especially those related to searching through data content.

Analysis of the state and trends in the development of methods for searching for visual information with query `ad exemplum` allows us to assert, despite numerous studies in this direction, the growth of the accumulated video data and the intensification of their use require the creation of new high-speed valid search tools.

The authors are specialists in the field of law, economics and IT, made an attempt to join forces to solve the problem of introducing digital technologies into the criminal process.The problem is extremely urgent today. The justice sector in general, and criminal justice in particular, requires modernization as a reaction to changing reality.The emergence of new technologies that can increase the efficiency of law enforcement, ensure the protection of individuals, society and the state, as well as the coronavirus pandemic, which has caused the need to limit physical contact between people, are factors that contribute to the search for new methods and tools for solving professional problems.

6. References

[1] Kryminalnyi protsecualnyi kodeks Ukrainy: Zakon Ukrainy № 4651-VI vid 13 кvitnia 2012 h. URL: https://zakon.rada.gov.ua/laws/ show/4651-17#Text [Criminal Procedure Code of Ukraine (2012)]

[2] Resolution 1604 (2008) Video surveillance of public areas. URL: https://pace.coe.int/en/files/17633/html

[3] M.V. Zavalnyi (2020). Shchodo zaprovadzhennia oboviazkovoi reiestratsii kamer videosposterezhennia, shcho spriamovani na publichni mistsia, ta poriadku otrymannia z nych informatsii URL: https://library.ppss.pro/index.php/ndippsn_20200221/article/view/zavalnyi

[M.V. Zavalnyi (2020). Regarding the introduction of mandatory registration of video surveillance cameras aimed at public places and the procedure for obtaining information from them].

[4] Lobach D. V., Mamychev A. Y., Miroshnichenko O. I., Moskvych L. (2021). Compreensão doutrinária do terrorismo cibernético no contexto do intenso desenvolvimento das tecnologias de informação e comunicação no mundo moderno. *Laplage Em Revista*, *7*(2), p.201-208. https://doi.org/10.24115/S2446-6220202172702p.201-208

[5] Mashtalir S., Mashtalir V. (2020) "Spatio-Temporal Video Segmentation.". In: Mashtalir V., Ruban I., Levashenko V. (eds) Advances in Spatio-Temporal Segmentation of Visual Data,. Studies in Computational Intelligence, vol 876. Springer, Cham, First Online: 17 December 2019, Part of the Studies in Computational Intelligence book series (SCI, volume 876), pp 161-210, https://doi.org/10.1007/978-3-030-35480-0_4

[6] L. Liung (1991). Identifikatsiia sistem. Teoriia dlia polzovatelia. *M.: Nauka,* 1991. 432 s. [Lennart Ljung (1991). System Identification. Theory for the User**].**

[7] Kaczmarz S. (1993). Approximate solution of system of linear equations. *International Journal of Control*. 1993. 57. No 5. P. 1269-1271.

[8] Ye.V. Bodianskii (2000). Adaptyvne vyiavlennia rozladnan v obiektakh keruvannia za dopomohoiu shtuchnykh neironnykh merezh. Dnipropetrovsk: *Systemni technologii*, 2000. 140 s. [E.V. Bodyansky (2000). Adaptive detection of disorders in control objects using artificial neural networks].

[9] S.V. Mashtalir, K.S. Shcherbinin (2010). Oblasti dostatochnosti i neobkhodimosti pri reshenii zadach alternativnogo poiska videodannykh. *Prikladnaia radioelektronika*. 2010. T. 9, # 4. S. 580-583. [S.V. Mashtalir, K.S. Shcherbinin (2010). Areas of sufficiency and necessity in solving problems of alternative search for video data].

[10] A.P. Mikhieiev (1983). Iterativnaia filtratsiia s reguliruiemym vzveshennym nakopleniiem informatsii. *Dinamicheskiie sistemy:upravleniie, adaptatsiia i optimizatsiia. Gorkii, 1983. S. 94-106.* [A.P. Mikheev (1983). Iterative filtering with adjustable weighted accumulation of information].

[11] S.V. Shilman (1983). Iterativnoie lineinoie otsenivaniie s reguliruiemym obiemom predistorii. *Avtomatika i telemechanika*. 1983. # 5. S. 93-98. [S.V. Shilman (1983). Iterative linear estimation with adjustable prehistory volume].

[12] E.Y. Chow (1980). Issues in the development of a general design algorithm for reli- able failure detection. *Proc. 19-th IEEE Conference on Decision and Control*. Albuquerque, 1980. P. 1006-1012.

[13] K.D. Liuis (1986). Metody prognozirovaniia ekonomichieskikh pokazatieliei. M.: Finansy i statistika, 1986. 133 s. [Lewis, Colin David (1986). Industrial and business forecasting methods].

[14] Yu.V. Chuiev (1975). Prognozirovaniie kolichestbennykh kharakteristik protsesov. M.: Sov. Radio, 1975. 400 s. [Yu.V. Chuiev (1975). Predicting the quantitative characteristics of processes].

[15] D.C. Montgomery (1990). Forecasting and time series analysis / D.C. Montgomery, I.A. Johnson, J.S. Yardiner. N.Y.: McGraw-Hill, 1990. 394 p.

[16] R.G. Brown (1963). Smoothing, forecasting, and prediction of discrete time series. N.Y.: Prentice Hall Inc., 1963. 468 p.

[17] D.W. Trigg (1967). Exponential smoothing with an adaptive response rate. *Operational Research*. 1967. Vol. 18, No 1. P. 53- 59.

[18] S.V. Mashtalir, K.S. Shcherbinin, S.V. Postulga (2010). Analiz rezultatov segmentatsii videodannykh. *Intellektualnnyie sistemy priniatiia reshenii i problem vychislitelnogo intellekta. (ISDMCI'2009)*: sb. nauchnykh trudov, Yevpatoriia, 17-21 maia 2010 g. Khierson: KhNTU, 2010. Tom 2. S. 431-435. [S.V. Mashtalir, K.S. Shcherbinin, S.V. Postulga (2010). Analysis of the results of the segmentation of video data].

[19] R. Izerman (1984). Tsifrovyie sistemy upravlieniia. M.: Mir, 1984. 541 s. [Isermann R. (1984). Digital control systems].

[20] K. Iberla (1980). Faktornyi analiz. M.: Statistika, 1980. 398 s. [Iberla, K. (1980). Factor analysis].

[21] Cichocki A. (1993). Neural networks for optimization and signal processing. Stuttgart: Teubner, 1993. 526 p.

[22] S.V. Mashtalir, K.S. Shcherbinin, S.V. Postulga (2010). Poisk izmienieniia stsen v videodannych na baze analiza rezultatov segmentatsii. *Bionika intellekta*. 2010. # 1. S. 65-69. [S.V. Mashtalir, K.S. Shcherbinin, S.V. Postulga (2010). Search for scene changes in video data based on the analysis of segmentation results].