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Removing Noise During the Filtering Images

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Abstract. ***In the problems of image recognition, various approaches used when the image is noisy and there is a small sample of observations. The article discusses the issue of noise filtering in image processing. The lack of a priori information complicates the processing of data, as a result of which it is necessary to rely on some statistical models of signals and noise. The use of known filters does not always give the desired result. A Gaussian filter can be used for additive noise, a modified Kalman filter eliminates a wider range of noise.***

Keywords: ***image, filtering, a set of binary images, a continuous algorithm, a discrete algorithm.***

I.INTRODUCTION

In the process of using the basic methods for processing video signals in conditions limited a priori data on the components of the data original signal, one inevitably has to rely on some statistical models of signals and noise. As a rule, the concepts of linearity, stationarity and normality of signals are used in the formation of these models.

At the input of the system, a sequence of frames I_n of some video V is supplied, which we represent in the following form

$$I_n = \{K_n(x,y), \quad 0 \le x < width, \quad 0 \le y < hight\}, \quad n = \overline{1,N}, \qquad (1)$$

here *width* of the frame, *height* of the frame, and $I_n(x, y)$ is a vector of fixed dimension. One approach to solving this problem is a set of image areas for each video frame in which one or more objects move. As a result of video processing, it is necessary to form a set of binary images in which white pixels (intensity 255) correspond to pixels belonging to moving objects, and black (intensity 0) correspond to background pixels (1) [1].

$$M_k(x,y) = \begin{cases} 255, & (x,y) - object\ pixel \\ 0, & (x,y) - pixel\ background \end{cases}, k = \overline{1,N}$$

It is required to assign each pixel to one of the classes. Class boundaries often overlap, which after applying the classifier (binarization operation) leads to the loss of sections of the desired objects and the presence of falsely selected sections of the background.

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Thus, under the conditions of a priori uncertainty regarding the brightness of the desired objects, it is impossible to select all objects in one frame at an acceptable level of classification errors, since regions of the same semantics are in different brightness ranges [2].

Noise reduction using a rectangular filter has a significant drawback: all the pixels in the filter mask at any distance from the processed have the same effect on the result [3-5]. A slightly better result is obtained by modifying the filter with an increase in the weight of the central point:

$$M_2^{low} \frac{1}{10}\begin{pmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{pmatrix}$$

More effective noise reduction can be achieved if the effect of pixels on the result decreases with increasing distance from the processed one. This property has a Gaussian filter with a core:

$$h(i,j) = \frac{1}{2\pi\sigma^2} e^{\frac{-(i^2+j^2)}{2\sigma^2}},$$

σ- dispersion.

A Gaussian filter has a nonzero kernel of infinite size. However, the values of filter core very quickly decrease to zero when moving away from the point *(0,0)*, and therefore, in practice, we can restrict ourselves to convolution with a small window around *(0,0)*, for example, taking the window radius equal to *3σ*. Gaussian filtering is also smoothing. However, unlike a rectangular filter, the image of a point in Gaussian filtering will have a symmetrical blurry spot, with a decrease in brightness from middle to edges. The degree of image blur is determined by the parameter σ. Gaussian filtering is used in conjunction with the Laplacian to emphasize boundaries.

Purpose of searching

To suppress local interference, median filters are used, the basis of which is an algorithm for enumerating and ordering array elements (one-dimensional or two-dimensional) in increasing or decreasing order. Such filters are non-linear mask-type filters [6-9]. The median is the value of the color that appears in the center of window as a result of rearrangements. In this case, the color of raster dot is replaced by value of color that is in the center. Impulse noise is suppressed, which suppresses local noise. Using a median filter, rounding of sharp corners occurs, reducing emissions and impulse noise, which is important when selecting contours. The selection of Kalman-type filter coefficients [10, 11] in a special way allows the filter to behave rationally: suppress noise and not increase dynamic filtering errors.

II.METHODS

When using the Kalman filter to solve the adaptive filtering problem, the monitored process is the vector of optimal filter coefficients.

In this case, the purpose of the Kalman filter is to minimize the variance σ of the estimate vector random process *x (k)*, which varies in time as follows:

$$\mathbf{x}(k+1) = \mathbf{\Phi}(k)\mathbf{x}(k) + \mathrm{v}(k), \quad (2)$$

here $\mathbf{\Phi}(k)$ is the transition matrix, v*(k)* is a random vector (process noise) having a normal distribution with the correlation matrix. A linearly transformed process *y(k)* is available for observation, to which observation noise is added:

$$\mathbf{y}(k) = \mathbf{H}(k)\mathbf{x}(k) + \mathbf{w}(k), \quad (3)$$

here *H(k)* is the observation matrix, *w(k)* is the observation noise, which is a random vector having a normal distribution with the correlation matrix.

The discrete input information processing algorithm in the framework of Kalman filtering methods has the form:

$$\mathbf{x}_0(k|k-1) = \mathbf{\Phi}(k)\mathbf{x}_0(k-1) + \mathbf{B}(k)U(k) + \mathbf{D}(k)\mathbf{F}(k);$$
$$\mathbf{x}_0(k) = \mathbf{x}_0(k|k-1) + \sum_{i=1}^{N}\mathbf{K}_i(k)\{z_i(k) - \mathbf{H}(k)\mathbf{x}_0(k|k-1)\};$$
$$\mathbf{K}_i(k) = S_i(k)P(k|k-1)\mathbf{H}^T\{\mathbf{H}(k)\mathbf{P}(k|k-1)\mathbf{H}^T(k) + \mathbf{V}_{vi}[k]\}^{-1};$$
$$\mathbf{P}(k|k-1) = \mathbf{G}(k)V_w(k)\boldsymbol{G}^T(k) + \boldsymbol{\Phi}(k)P(k-1)\mathbf{\Phi}^T(k);$$
$$\mathbf{P}(k) = \mathbf{P}(k|k-1) - \sum_{i=1}^{N}\mathbf{K}_i(k)\mathbf{H}(k)\mathbf{P}(k|k-1),$$
$$i = 1, \ldots, N,$$

here z_i *(k)* is the observation vector; $z_0 = \mathbf{H}(n)\mathbf{x}_0(n|n-1)$ is the vector of observation estimates; $\mathbf{x}_o$ *(n)* is the state vector estimate; $\mathbf{x}_o(k|k\text{-}1)$ - estimation of the state forecasting vector; $\mathbf{\Phi}$ (k) is a transition matrix; H (k) is the observation matrix; $K_i(k)$ - matrix of coefficients; $\mathbf{P}(k|k\text{-}1)$ is the dispersion matrix of the state vector; ***P(k)*** is the dispersion matrix for estimating the state vector; *U(k)* is the control vector; ***F(k)*** is the vector of measured signals from the output of the object; *B(k)* is the matrix of control coefficients; *D(k)* is the matrix of measurement coefficients; $S_i(k)$ - a sign of the type of meter or lack of measurements; $S_i(k) = 0$ [10].

III.DATA COLLECTION AND ANALYSIS

The continuous Kalman filtering algorithm in time has the form [12,13]:

$$\frac{d\mathbf{x}_0}{dt} = \Phi(t)\mathbf{x}_0(t) + \mathbf{B}(t)U(t) + \mathbf{D}(t)\mathbf{F}(t) + \sum_{i=1}^{N}\mathbf{K}_i(t)(z_i(t) - \mathbf{H}(t)\mathbf{x}_0(t);$$
$$\frac{dP(t)}{dt} = V_w(t) + \Phi(t)\mathbf{P}(t) + \mathbf{P}(t)\Phi^T(t) - \mathbf{P}(t)\mathbf{H}^T(t)V_v^{-1}(t)\mathbf{H}(t)\mathbf{P}(t), \quad (4)$$

where $z_i(t)$ is the observation vector; $z_o(t) = H(t)\,x_o(t)$ is the vector of estimates of observations; $x_o(t)$ is the state vector estimate; $\Phi(t)$ is a transition matrix; *P(t)* is the correlation matrix; *H(t)* is the observation matrix; $\mathbf{K}_i(t) = S_i(t)\mathbf{P}(t)\mathbf{H}^T(t)V_{vi}^{-1}(t)$ - matrix of coefficients; *U(t)* is the control vector; *F(t)* is the vector of measured signals from the output of the object; *B(t)* is the matrix of control coefficients; *D(t)* is the matrix of measurement coefficients; $S_i(t)$ is a sign of the type of meter or the absence of measurements

$S_i(t) = 0$.

The predicted value of the observed signal: $\hat{\mathbf{y}}(k) = \mathbf{C}(k)\Phi(k)\hat{\mathbf{x}}(k-1)$. The difference or discrepancy between predicted and actually observed signals:

$$e(k) = \mathbf{y}(k) - \hat{\mathbf{y}}(k), \quad (5)$$

then $\mathbf{P}(k-1)\mathbf{C}^T(k) \times \left(\mathbf{C}(k)\mathbf{P}(k-1)\mathbf{C}^T(k) + \mathbf{Q}_M(k)\right)^{-1} = \mathbf{K}(k)$ - Kalman gain [14].

Extrapolation of the state vector of the system according to the state vector estimate and applied to the control vector from step (k−1) to step k: $\hat{\mathbf{x}}(k) = \mathbf{\Phi}(k)\hat{\mathbf{x}}(k-1) + \mathbf{K}(k)\mathrm{e}(k)$ is the posterior estimate of the state vector for the k^th frame, the dimension of vector is determined by order of filter (Fig. 1).

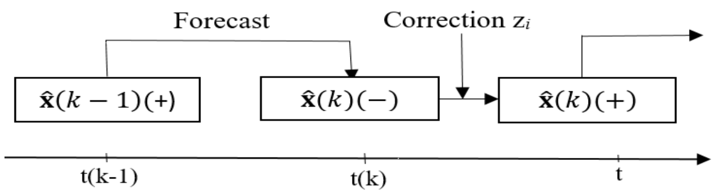

Fig.1. Kalman filter operation in step (k-1)

Updating the estimation of the correlation matrix of filtering errors has the form [14]:

$$\mathbf{P}(k) = \mathbf{\Phi}(k)[\mathbf{P}(k-1) - \mathbf{K}(k)\mathbf{C}(k)\mathbf{P}(k-1)]\mathbf{\Phi}^T(\mathrm{k}) + \mathbf{Q}_M(k),$$

$\mathbf{Q}_M(k)$ - covariance matrix of some random variable; therefore, its trace is non-negative. The trace minimum is reached when the last term is zeroed:

$$\mathbf{K}(k) = \mathbf{P}(k-1)\mathbf{H}^T(k)S^{-1}(k) \quad (6)$$

This matrix is the desired one and, when used as a matrix of coefficients in the Kalman filter, it minimizes the sum of the mean square errors of the state vector estimate.

It is assumed that there are no deterministic changes in the coefficients; therefore, the transition matrix **Φ** is unit: **Φ**(k) = I. The observation matrix is the vector of the content of the filter delay line *u*(k). Thus, the filter output signal is the predicted value of the observed signal, and the exemplary adaptive filter signal *d*(k) acts as the observed signal itself. In this case, the observation noise is an error in reproducing an exemplary signal, and the Q_M matrix turns into a scalar parameter the mean square error signal [12,13].

IV.DATA ANALYSIS STRATEGY

If a stationary random process is filtered, the coefficients of the optimal filter are constant and $Q_p = 0$ can be taken. To enable the filter to track slow changes in the statistics of the input signal, a diagonal matrix can be used as the covariance matrix $\mathbf{Q}_p$. As a result, the above formulas (2-4) take the following form:

$\mathbf{y}(k) = \mathbf{u}^T(k)\hat{\mathbf{w}}(k-1)$ - a posterior filter output signal (predicted value of the reference signal);

$\mathrm{e}(k) = d(k) - \mathbf{y}(k)$ - filter residual;

$\mathbf{K}(k) = \frac{\mathbf{P}(k-1)\mathbf{u}(k)}{\mathbf{u}^T(k)\mathbf{P}(k-1)\mathbf{u}(k)+\mathbf{Q}_M}$ - Kalman gain;

$\widehat{\mathbf{w}}(k) = \widehat{\mathbf{w}}(k-1) + \mathbf{K}(k)\mathrm{e}(k)$- estimates of filter coefficients;

$\mathbf{P}(k) = \mathbf{P}(k-1) - \mathbf{K}(k)\mathbf{u}^T\mathbf{P}(k-1) + \mathbf{Q}_p$- estimation errors.

The initial value of the vector w is usually taken to be zero, and the diagonal matrix is used as the initial estimate of the matrix **P** [14].

Applying the considered algorithm to the image, we obtained the characteristics and the image of the binary form - Fig. 2.

Fig. 2. The result of applying the Kalman filter [14]

V.DISCUSSION

When using the Kalman filter to solve adaptive filtering problem, the monitored process is the vector of coefficients optimal filter **w**. It is assumed that there are no deterministic changes in the coefficients; therefore, the transition matrix **Φ** is the identity matrix: **Φ**(*k*) = **I**. The observation matrix is the vector of the content filter delay line **u** (k). Thus, the filter output is predicted value of the observed signal, and model signal of the adaptive filter *d (k)* acts as the observed signal itself. In this case, the observation noise is an error in reproducing an exemplary signal, and the matrix $Q_{M\ turns}$ into a scalar parameter the mean square of the error signal.

When processing images with a Kalman filter of a block form, 3x3 and 4x4 blocks were used. The Q_M error covariance matrix is constantly updated. The results of image processing and the standard deviation of the error were obtained (Fig. 3). The gain of the Kalman filter is obtained based on the covariance matrix, which minimizes the sum of mean square errors of the state vector estimate. In this case, the filter output signal represents predicted value of observed signal, and the model signal of adaptive filter acts as the observed signal itself.

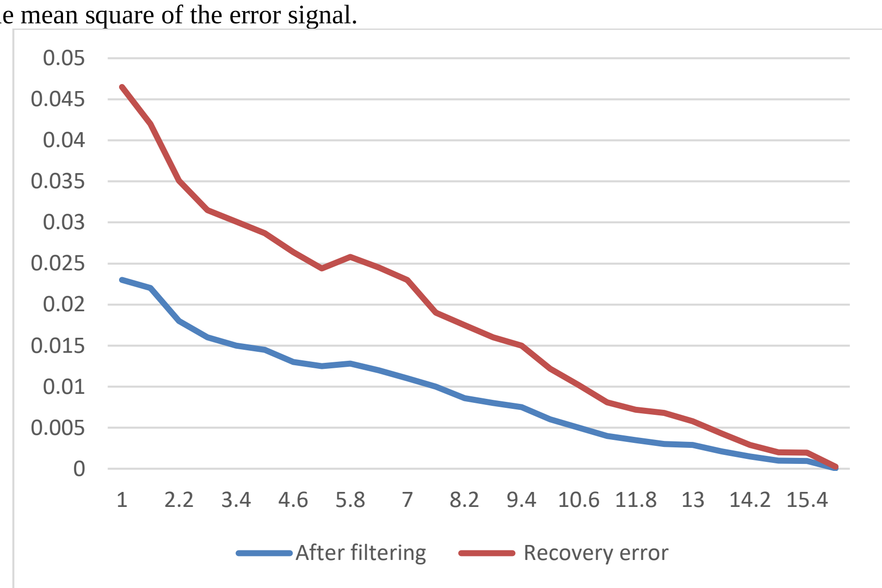

Fig. 3. The graph of the mean square error between the original and the restored image.

The graph shows the result of restoring video images as new images arrive. After 16 images, the results coincided, the value of the standard deviation was σ = 0,05.

If a stationary image is filtered, the coefficients of the optimal filter are constant and $Q_p = 0$ can be taken.

VI.CONCLUSION

Using the Kalman filter, objects necessary for processing in the recognition process were selected, some of the objects were deleted. This is one of the disadvantages of the Kalman filter associated with the high sensitivity of the resulting estimate with respect to the influence of abnormal effects such as abnormal observations, shadowing of objects, and the occurrence of affected areas of images. When processing images with the Kalman filter, a problem arose due to the large size of the system matrices, which accordingly led to an increase in the time and volume of calculations, as well as the consumption of computing resources.

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