UDC 004

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IMAGE SEGMENTATION IN COMPUTER VISION DIAGNOSTIC SYSTEMS

Annotation. *Applicability image segmentation approaches for image segmentation for actual diagnostic task are studied in the work. Abnormal patient's neurotic-tremor moves analysis and identification hybrid model is described in article.*

Keywords: *segmentation, identification, diagnostic IT model*

1. Introduction

The last 50 years in our technology-oriented society has become such a situation in which more and more people and organizations are engaged in processing information and less – in the processing of material objects. There are tendencies that by the year 2030 the machines will disappear dozens of professions that serve data input. Computer technology is so firmly rooted in our society that today it is impossible to imagine any kind of activity is not connected, one way or another, with a computer [3].

Summarizing the survey of researches and implementation of intellectual IT in the EU and the US: Through FP7 and Horizon 2020, the EU funded the development of sophisticated techniques for understanding audiovisual projections throughout life for typical and non-typical populations. It is believed that robotic input systems that are integrated into the body with the hands and feet are the near future of computer vision. And this will require the development of models and methods for the synthesis of methods for the reception of visual spectrum data, obtained in real time [2,4]. Thus, the actual problem of the development of artificial intelligence is the development of the principles of computer perception of the outside world through the understanding of video data [1,5].

Industry 4.0 leads us to another informational explosion. And the human brain and society itself can not control this information explosion - we need more advanced information systems that will carry out the lion's share of information processing. Because information it is a key element of the decision-making process. In addition, quantity of varied and different levels of complexity of information that our world generates is spin-off, so we need adaptive information input systems. That is, such

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that humans will not to interfere with their work when changing external conditions - the systems themselves must be re-configured.

In particular, the development of Cyber-Physical Systems perception of the external world by people with disabilities in the visual spectrum is relevant today. This applies to both congenital (eg, congenital blindness) and acquired conditions (for example, with age or as a result of an accident). Today, implant technologies allow sensors to transmit information to the retina of the eye, so researching the methods and ideas of allocating a useful signal in real time is extremely relevant.

2. Formulation of the problem

Main task it is primary automatic diagnosis by information analytic system (IAS). The IAS needs to recognize abnormal, untypical patient condition. Method bases on recognizing week control of writing (fig 1).

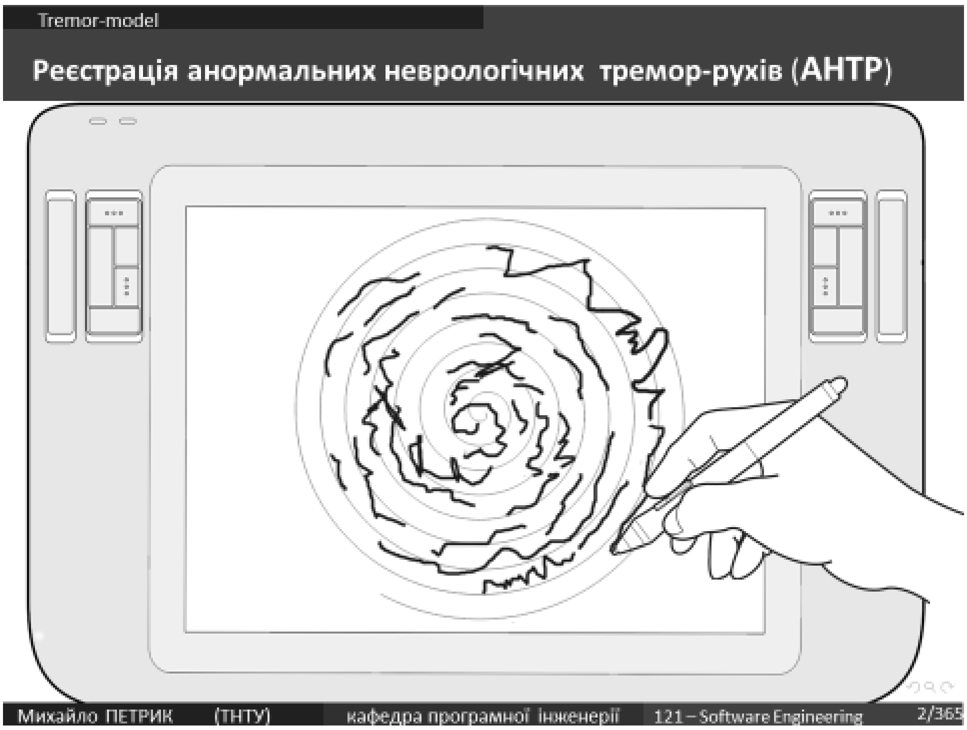

Fig. 1. Visualization of Idea of week write control.

Therefore, we describe separate our problem on some tasks: segmentation and recognition.

3. Main approaches to objects selection on task area

For our problem (Computer vision systems in real-time), we will investigate several main groups of threshold approaches that work effectively in real time.

3.1. Binarization methods with global threshold

1. *Binaryization with lower threshold.*

Binaryization with a lower threshold method refers to a group of image segmentation methods based on global thresholds.

The essence of the method is that the global brightness threshold is selected as a certain constant, and, depending on the ratio of this constant to the local brightness values for each pixel, the binary value of this pixel. This method is the most simple and widespread. The method is effective for standard conditions. We describe it as follows:

$$a_{xy}^{new} = \begin{cases} 0, if \ \frac{r+g+b}{3}(a_{xy}) \le L \\ 1, if \ \frac{r+g+b}{3}(a_{xy}) > L \end{cases}, \quad (3.1)$$

here a_{xy}^{new} – the resulting value of the brightness of the pixel;

a_{xy} – input value of pixel brightness;

$L(const) \in [0, 255]$ – global lighting level;

r, g, b – The original values of the red, green, and blue component of the a_{xy} pixel color.

3.2. Binarization methods with local threshold

3.2.1. Niblak method

The method is based on the calculation of the local threshold of illumination.

The idea is to align the threshold of brightness of binaryization from point to point based on the deviation of the local mean brightness value (the value calculated for each pixel based on the brightness values of itself and its neighbors), from the local (calculated for only one pixel) in the given mask [6].

That is, the binary representation of the pixel is computed as follows:

$$a_{xy}^{new} = \begin{cases} 0, \ if \ B(x,y) \le L \\ 1, \ if \ B(x,y) > L \end{cases}, \quad (3.2)$$

here $B(x,y) \in [0,255] = \frac{r+g+b}{3}(a_{xy})$, – local pixel brightness value a_{xy};

$L \in [0,255] = m_{w\times w}(x,y) + k * s_{w\times w}(x,y)$ – local brightness threshold for pixel a_{xy} in the $w \times w$ district;

$m_{w\times w}(x,y) \in [0,255] = \frac{\sum_1^{w\times w} B(x,y)}{w\times w}$ – the average brightness value in the $w \times w$ district of the pixel (x,y);

$s_{w\times w}(x,y) = \sqrt{\frac{1}{w\times w}\sum_{1}^{w\times w}(B(x,y) - m_{w\times w}(x,y))^2}$ – Mean square deviation of the sample in the district of the pixel;

$k(const) = -0{,}2$ for objects that are more likely to be represented in black (namely if $B(x,y) \leq 127$), and $k = 0{,}2$ For objects that are more likely to be white $B(x,y) > 127$;

$w(const)$ – mask size of district, for example, 15[6].

3.4. Methods with perticial thresholds preprocessing

This method exeprs background pixel britness values:

$$a_{xy}^{new} = \begin{cases} 0, & if\ B_{x,y} > L \\ f(y,x), f(x,y), & if\ B_{x,y} \leq L \end{cases}, \quad (3.4)$$

3.6.3. Otsu method.

The method uses a histogram of the distribution of the brightness values of the pixels of the image

The essence of the Otsu method is to set the threshold between classes on a histogram in such a way that each of them is as "dense" as possible. If expressed in a mathematical language, then this is reduced to minimizing the intra-class variance, which is defined as the weighted sum of dispersions of the two classes:

$$\sigma_w^2(L) = w_1(L)\sigma_1^2(L) + w_2(L)\sigma_2^2(L), \quad (3.6.3.1)$$

де weight w_i – this is the probability of two classes separated by the threshold L;

σ_i^2 – dispersion of these classes.

Otsu proved that minimizing the dispersion inside the class is equivalent to maximizing the dispersion between classes, which can be expressed through the probability w_i and the arithmetic mean μ_i:

$$\sigma_b^2(L) = \sigma^2 - \sigma_w^2(L) = w_1(L)w_2(L)[\mu_1(L) - \mu_2(L)]^2. \quad (3.6.3.2)$$

At first we need to build histogram $p(l)$ of image and determine the entries rate $N(l)$ of every brightness level at image $G(x,y)$. We are looking for total brightness N_T of image pixels:

$$N_T = \sum_{i=0}^{\max(G)} p(i) \quad (3.6.3.3)$$

Then for each value of the half-ton (threshold) $L = \overline{1, max(G)}$ we perform the following:

$$\omega_1(L) = \frac{\sum_{i=0}^{L-1} p(i)}{N_T} = \sum_{i=0}^{L-1} N(i), \qquad \omega_2(L) = 1 - \omega_1(L) \quad \textbf{(3.6.3.4)}$$

$$\mu_T = \frac{\sum_{i=0}^{\max(G)} i * p(i)}{N_T} = \sum_{i=0}^{\max(G)} i \times N(i) \quad \textbf{(3.6.3.5)}$$

$$\mu_1(L) = \frac{\sum_{i=0}^{L-1} i * p(i)}{N_T * w_1(L)} = \frac{\sum_{i=0}^{L-1} i \times N(i)}{w_1(L)}, \qquad \mu_2(L) = \frac{\mu_T - \mu_1(L) \times w_1(L)}{w_2(L)} \quad \textbf{(3.6.3.6)}$$

$$\sigma_b^2(L) = \sigma^2 - \sigma_w^2(L) = w_1(L) w_2(L)[\mu_1(L) - \mu_2(L)]^2. \quad \textbf{(3.6.3.7)}$$

The wanted threshold is equal to L, at which $\sigma_b^2(L)$ is equal to maximum:

$$L = argmax_L \, \sigma_b^2(L) \quad \textbf{(3.6.3.8)}$$

Binary pixel representation is calculated as:

$$a_{xy}^{new} = \begin{cases} 0, \ if \ B(x,y) \le L \\ 1, \ if \ B(x,y) > L \end{cases}. \quad \textbf{(3.6.3.9)}$$

<u>3.6.4. *Triangle method*</u>

The method uses a histogram of the distribution of brightness values in the image (graphically shown in Figure 2).

We build line s on the histogram from minimal brightness value b_{min} to maximum brightness value b_{max}. The threshold will be defined the element of the histogram, the distance from which to s is greatest [9]:

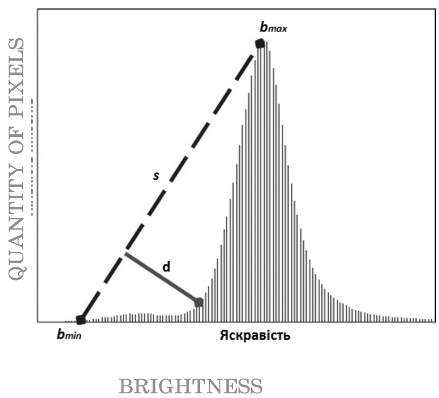

Fig.2. Triangle method

$$L = argmax_{b(i)} d, \quad \textbf{(3.6.4.1)}$$

where

L – threshold value;

d – distance from histogram value$b(i)$ to line s.

Binarization we realize by standard formula:

$$a_{xy}^{new} = \begin{cases} 0, if\ B(x,y) \le L \\ 1, if\ B(x,y) > L \end{cases} \quad (3.6.4.2)$$

3.6.5. The threshold based on the gradient of brightness determining method

Let pixels of the image can be divided into two sets (two classes) – pixels belonging to the set of objects and pixels belonging to the set of background. Then, the algorithm for calculating the threshold is the following two steps:

1) The brightness gradient module for each pixel is determined:

$$G(m,n) = \max\{|G_m(m,n)|, |G_n\ (m,n)|\} \quad (3.6.5.1)$$

here $G_m(m,n) = f(m+1,n) - f(m-1,n)$;

$$G_n\ (m,n) = f(m,n+1) - f(m,n-1).$$

2) Threshold is calculated as:

$$t = \frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f(m,n)G(m,n)}{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} G(m,n)} \quad (3.6.5.2)$$

here t –threshold value.

3.7. Methods of binarization using color brightness entropy

3.7.1. Yen's method

This method refers to methods that use the entropy of the distribution of the brightness of colors in the image. Yen's method looks at the object on the images and the background on which this object is located, as two different sources of visual information. And the value of brightness, in which the sum of these two entropies reaches their maximum, is considered the optimum threshold for image segmentation [8].

To begin, we need to calculate the histogram $p(l)$ of the image and the input frequency $N(l)$ of each brightness level of the image $G(x,y)$. We also look for the total brightness of N_T image pixels:

$$N_T = \sum_{i=0}^{\max(G)} p(i) \quad (3.7.1)$$

We are building auxiliary normalized histograms:

$$p_{norm}(i) = \frac{p(i)}{N_T}, \quad (3.7.2)$$

$$p_{normC}(i) = p_{normC}(i-1) + p_{norm}(i), \quad (3.7.3)$$

$$p'_{norm}(i) = p'_{norm}(i-1) + p_{norm}(i)^2, \qquad (3.7.4)$$

$$p''_{norm}(i) = p''_{norm}(i+1) + p_{norm}(i+1)^2, \qquad (3.7.5)$$

We find the entropy of the object and its background:

$$C_f(T) = -\log\{p_{normC}(i) \times (1 - p_{normC}(i))\}. \qquad (3.7.6)$$

$$C_b(T) = -\log\{p'_{norm}(i) \times p''_{norm}(i)\}. \qquad (3.7.7)$$

Determine the value of i, when the sum of these entropies is maximal:

$$L = argmax_i \{C_b(T) + C_f(T)\}. \qquad (3.7.8)$$

We use this value as the threshold of brightness and binaryize the image:

$$a_{xy}^{new} = \begin{cases} 0, if\ B(x,y) \le L \\ 1, if\ B(x,y) > L \end{cases} \qquad (3.7.9)$$

4. Model

On the next step, input vector is presented in 3D visualization (fig.3).

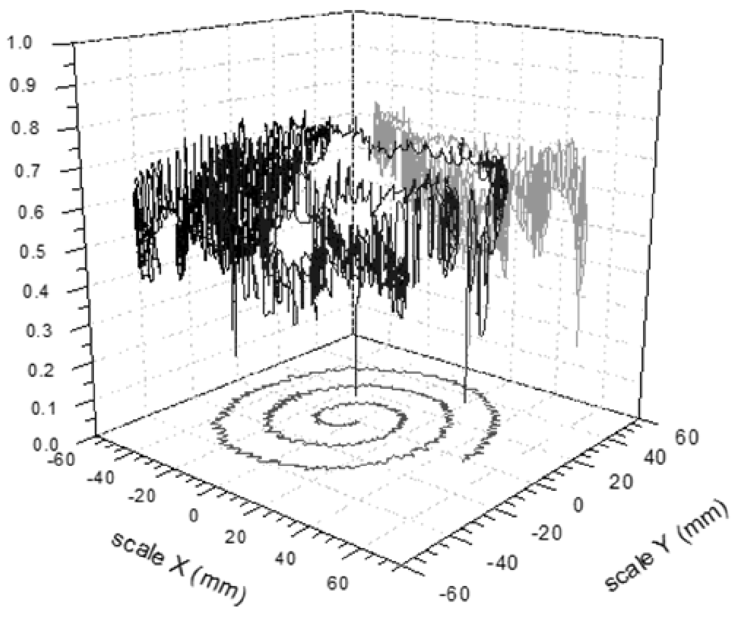

Fig.3. 3D visualization.

We describe trajectory as Set of digital elements:

$$I_{n_1} = \left\{ z \in \bigcup_{k=1}^{n_1+1} (l_{k-1}, l_k),\ 0 \le l_0 < l_{n_1+1} < \infty \right\}$$

$$u_j(t,z) = \int_0^t \sum_{k=1}^{n_1+1} \int_{l_{k-1}}^{l_k} \mathcal{H}_{jk}(t-\tau, z, \xi) \left[\sum_{i=1}^{n_2+1} \sigma_{ij} S_i(\tau, \xi) \right] d\xi d\tau, \quad _{j=\overline{1,n_1+1}}$$

The recall matrix of system: for the any j-th element of the working trajectory at time t when the k-th impulse is signaled from the sensors of the i-th set of neural nodes of the cerebral cortex:

$$\mathcal{H}_{jk}(t,z,\xi)=\sum_{m=1}^{\infty}\frac{\sin q_m t}{q_m}\frac{V_j(z,\beta_m)V_k(\xi,\beta_m)}{\left\|V(z,\beta_m)\right\|^2};\quad {}_{j,k=\overline{1,n+1}}$$

where

$\mathrm{P}=\left[\sigma_{ij}\right],\ {}_{i=\overline{1,n_2},\ j=\overline{1,n_1}}$ - it is interface matrix of connection between $\mathcal{H}_{jk}$ elements and neural networks impulses from sensors S_i of neural nodes of the brine.

The hybrid spectral vector-function components $V(z,\beta_m)$ are:

$$\begin{bmatrix} V_1(z,\beta_m) \\ \dots \\ V_k(z,\beta_m) \\ \dots \\ V_{n_1+1}(z,\beta_m) \end{bmatrix}=\begin{bmatrix} \left(\prod_{i=1}^{n_1}\xi_{i+1}\frac{\beta_m}{b_{i+1}}\right)\omega_0^2(\beta_m)\vartheta_1^{11}\left(\frac{\beta_m}{b_1}z\right)-\omega_0^1(\beta_m)\vartheta_1^{21}\left(\frac{\beta_m}{b_1}z\right) \\ \dots \\ \left(\prod_{i=k}^{n_1}\xi_{i+1}\frac{\beta_m}{b_{i+1}}\right)\omega_{k-1}^2(\beta_m)\vartheta_k^{11}\left(\frac{\beta_m}{b_k}z\right)-\omega_{k-1}^1(\beta_m)\vartheta_k^{21}\left(\frac{\beta_m}{b_k}z\right),\ {}_{k=\overline{2,n}} \\ \dots \\ \omega_{n_1}^2(\beta_m)\vartheta_{n_1+1}^{11}\left(\frac{\beta_m}{b_{n_1+1}}z\right)-\omega_{n_1}^1(\beta_m)\vartheta_{n_1+1}^{21}\left(\frac{\beta_m}{b_{n_1+1}}z\right) \end{bmatrix}$$

here

$\{\beta_m\}_{m=1}^{\infty}$ - it is set of hybrid vector-function components spectral values

$\left\{\vartheta_k^{11}\left(\frac{\beta_m}{b_k}z\right),\ \vartheta_k^{21}\left(\frac{\beta_m}{b_k}z\right)\right\},\ k=\overline{1,n_1+1}$ - it is basis function set of hybrid vector-function components.

The model of abnormal neurotic-tremor moves is shown by transcendental equation of spectral values β_m jf vector function $V(z,\beta_m)$:

$$\omega_{n_1}^2(\beta)\vartheta_{n_1+1}^{11}\left(\frac{\beta}{b_{n_1+1}}l_{n_1+1}\right)-\omega_{n_1}^1(\beta)\vartheta_{n_1+1}^{21}\left(\frac{\beta}{b_{n_1+1}}l_{n_1+1}\right)=0$$

here

$$\omega_k^j(\beta)=\omega_{k-1}^2(\beta)\psi_{1j}^k\left(\frac{\beta}{b_k}l_k,\frac{\beta}{b_{k+1}}l_k\right)-\omega_{k-1}^1(\beta)\psi_{2j}^k\left(\frac{\beta}{b_k}l_k,\frac{\beta}{b_{k+1}}l_k\right)$$

$$\psi_{ij}^{k}\left(\frac{\beta}{b_k}l_k,\frac{\beta}{b_{k+1}}l_k\right)=\vartheta_k^{i1}\left(\frac{\beta}{b_k}l_k\right)\vartheta_k^{j2}\left(\frac{\beta}{b_{k+1}}l_k\right)-\vartheta_k^{i2}\left(\frac{\beta}{b_k}l_k\right)\vartheta_k^{j1}\left(\frac{\beta}{b_{k+1}}l_k\right),\quad i,j=\overline{1,2},\ k=\overline{1,n}$$

$$\vartheta_k^{12}\left(\frac{\beta}{b_s}l_k\right)=-\xi_s\frac{\beta}{b_s}\vartheta_k^{21}\left(\frac{\beta}{b_s}l_k\right),\qquad \vartheta_k^{22}\left(\frac{\beta}{b_s}l_k\right)=\xi_s\frac{\beta}{b_s}\vartheta_k^{11}\left(\frac{\beta}{b_s}l_k\right),\quad s\in\{k,k+1\}$$

$$\omega_0^1(\beta)=-\vartheta_0^{11}\left(\frac{\beta}{b_1}l_0\right);\qquad \omega_0^2(\beta)=-\vartheta_0^{21}\left(\frac{\beta}{b_1}l_0\right),$$

Conclusions

Applicability image segmentation approaches for image segmentation for actual diagnostic task are studied. In addition, the recognition procedure is optimized. Abnormal patient's neurotic-tremor moves analysis and identification hybrid model is described in article.

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