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## ANALYSIS OF MOTION DETECTION IN VIDEO FOR EARLY FOREST FIRE DETECTION

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*Reliable and early detection of forest fire can significantly reduce the damage caused to forestry. Using of machine vision systems, namely video fire detectors, belongs to promising area forest fire recognition. Motion detection is the key step for smoke and flame monitoring in video. This document describes some methods of movement detection in video sequences, including comparative analysis of opportunities to find moving regions, their advantages and disadvantages.*

Forest fires are one of the main problems in regions with hot climate and extensive vegetation. The work in [1] reports that, each year, about 0.1% of the world forest surface is destroyed by fires. In most cases, manned surveillance towers are adopted to watch forest areas which present the greatest risk of fire. Lookout towers equipped with cameras are a more feasible approach, since many cameras from different locations and points of view can be monitored by a single control station.

Recently, many research projects have studied the possibility to develop automatic fire and smoke detection systems based on sensor networks or machine vision techniques, in order to achieve a better efficiency and a shorter alarm response time. These approaches have the advantages of a great distance vision, absence of latency, and the possibility to extract more information (such as position, size, growth, and kind of fire and smoke) [2].

This article presents a comparative analysis of moving regions detection methods in order to identify their strengths and weaknesses.

Two approaches to detect moving objects in video images are commonly used now: background subtraction methods [3, 4] and the Gaussian mixture model based on background subtraction methods [5, 6].

Using background subtraction methods is the most common approach to detect moving regions in the video image, obtained using a stationary camera. The essence of these methods is the per-pixel comparison of the current frame with a pattern that is usually named as a background model. Background model, which is a description of the scene without moving objects, must be constantly updated to reflect the changes that are not associated with the movement of objects.

In most cases the adaptive system is used to evaluate the background and threshold values. The background estimation is computed as follows:

$$B(x,y,t+1) = \begin{cases} aB(x,y,t) + (1-a)I(x,y,t), \text{if } (x,y) \text{ stationary} \\ B(x,y,t), \text{is a moving pixel} \end{cases}$$

where $I(x; y; t)$ represents the intensity of the pixel at location $(x; y)$ in the $t$-th frame of the frame sequence $I$, $B(x; y; t)$ is the previous estimated background intensity at the same pixel position, $a$ – is a positive real constant close to one. Initially, $B(x; y; 0)$ is set equal to the first frame $I(x; y; 0)$.

The motion detection of a pixel is determined as follows. A pixel positioned at $(x; y)$ is assumed to be moving if it satisfies the disequations:

$$|I(x,y,t) - I(x,y,t-1)| > T_I(x,y,t)$$
$$|I(x,y,t) - I(x,y,t-2)| > T_I(x,y,t)$$

where $I(x; y; t-1)$ is the intensity of the pixel at the location $(x; y)$ in the $(t-1)$-th frame I and $T_I(x; y; t)$ is a threshold updated at each frame, according to the equation:

$$T_I(x,y,t+1) = \begin{cases} bT_I(t) + (1-b)(c|I(x,y,t) - B(x,y,t)|), \text{if } (x,y) \text{ stationary} \\ T_I(t), \text{if } (x,y) \text{ is a moving pixel} \end{cases}$$

where $c$ is a real constant greater than one and $b$ is a positive constant close to one. Initial threshold values are set to a predetermined non-zero value. In order to detect even slow moving regions, as described in [3], it is possible to use two different background estimations, $B^{fast}(x; y; t)$ and $B^{slow}(x; y; t)$. $B^{fast}(x; y; t)$ is updated at every frame and $B^{slow}(x; y; t)$ is updated every second. For every pixel $(x; y)$, the value $D_M(x; y; t)$ representing its motion is computed as follows:

$$D_M = \begin{cases} 0, & if\left|B^{fast} - B^{slow}\right| \le T_{low} \\ \dfrac{\left|B^{fast} - B^{slow}\right| - T_{low}(t)}{T_{hight} - T_{low}} & if \;\; T_{low} \le \left|B^{fast} - B^{slow}\right| \le T_{hight} \\ 1 \; if \; T_{hight} \le \left|B^{fast} - B^{slow}\right| \end{cases}$$

where $0 < T_{low} < T_{hight}$ are threshold values. The result is a matrix $D_M\ (x,y)$ with values in the range $[0;\ 1]$. The resulting matrix $D_M$ is threshold in order to reduce the computational time and by considering regions with low values of movement.

This approach is simple and fast method for determining the motion in the video sequence. However, since it is using the frame difference, then it is characterized by all the shortcomings of the frame difference method: high sensitivity to noise and inaccurate reproduction of the form of moving objects.

A technique of moving object detection, that recently became popular, is a Gaussian mixture model based on the method of background subtraction [5].

In order to adapt to the changes, you will need to update the training set by adding new samples and discarding old ones.

Selects a reasonable time period *T* and at time t we have: $X_T = \{x^t, \dots, x^{(t-T)}\}$. For each new sample is updated set of training data $X_T$ and reestimate $p(x|X_T, BG)$. However, among the samples from the recent history there could be some values that belong to the foreground objects and the need to mark this estimate as $p(x^{(t)}|X_T, BG + FG)$. Using GMM with *M* components:

$$p\left(x^{(t)}\middle|X_T, BG + FG\right) = \sum_{m=1}^{M} \pi_m N(x; \mu_m, \sigma_m^2 I)$$

where $\mu_1, \dots, \mu_M$ are the estimates of the means and $\sigma_1, \dots, \sigma_M$ are the estimates of the variances that describe the Gaussian components. The covariance matrices are assumed to be diagonal and the identity matrix, I has proper dimensions. The mixing weights denoted by $\pi_m$ are non-negative and add up to one. Given a new data sample $x^{(t)}$ at time t the recursive update equations are [6]:

$$\pi_m \leftarrow \pi_m + \alpha\left(o_m^{(t)} - \pi_m\right)$$
$$\mu_m \leftarrow \mu_m + o_m^{(t)}(\alpha/\pi_m)\delta_m$$
$$\sigma_m^2 \leftarrow \sigma_m^2 + o_m^{(t)}\left(\frac{\alpha}{\pi_m}\right)(\delta_m^T \delta_m - \sigma_m^2),$$

where $\delta_m = x^{(t)} - \mu_m$. Instead of the time interval T, that was mentioned above, here constant $\alpha$ describes an exponentially decaying envelope that is used to limit the influence of the old data. Retaining the same notation having in mind that approximately $\alpha$= 1\T. For a new sample the ownership $o_m^{(t)}$ is set to 1 for the 'close' component with largest $\pi_m$, and the others are set to zero. Define that a sample is 'close' to a component if the Mahalanobis distance from the component is for example less than three standard deviations. The squared distance from the m-th component is calculated as: $D_m^2\left(x^{(t)}\right) = \delta_m^T\, \delta_m/\sigma_m^2$ . If there are no 'close' components a new component is generated with $\pi_{M+1} = \alpha, \mu_{M+1} = x^{(t)}$ и $\sigma_{M+1} = \sigma_0$, where $\sigma_0$ – is some appropriate initial variance. If the maximum number of components is reached we discard the component with smallest $\pi_m$.

The presented algorithm presents an on-line clustering algorithm. Usually, the intruding foreground objects will be represented by some additional clusters with small weights $\pi_m$. Therefore, can be approximate the background model by the first *B* largest clusters:

$$p\left(x^{(t)}\middle|X_T, BG\right) = \sum_{m=1}^{M} \pi_m N(x; \mu_m, \sigma_m^2 I)$$

If the components are sorted to have descending weights $\pi_m$, we have:

$$B = \arg\min_b\left(\sum_{m=1}^{b} \pi_m > (1 - c_f)\right)$$

where $c_f$ – is a measure of the maximum portion of the data that can belong to foreground objects without influencing the background model.

Using the Gaussian mixture distribution to present the background model has a list disadvantages. Firstly, the method is not adapted to passing changes in light, that is natural for some videos. Second, the initialization of distribution parameters is time-consuming.

A relatively large number of parameters requires selection of the most optimal values for specific data.

This document contains a comparative analysis of existing methods of automatic detection of moving smoke areas on video sequences. Noted, that the most popular methods of motion detection methods are based on background subtraction. Gaussian mixture model based on the method of background subtraction solves the problem to noise and inaccurate reproduction of moving objects' forms, but it is not adopted to rapid changes in lighting as well as the distribution parameters initialization is rather time-consuming procedure. Thus, refining of the algorithms in predetermined directions is needed to improve the detection of moving areas.

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## MODELING ELLIPTICAL SLOT ANTENNA IN THE PROGRAM HIGH FREQUENCY SYSTEM SIMULATOR

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*This article presents the results of modeling an elliptical slot antenna in the software High Frequency System Simulator (HFSS). It was investigated the dependence the characteristics of the antenna on the change in thickness of the substrate. For research as substrate material is selected the dielectric with permittivity $\varepsilon = 3$, thickness of 1.575 mm, 2 mm, 3 mm. The results are presented in the graphs: the standing wave ratio (SWR), polar pattern, input impedance. It shows the structure of the antenna with the description of its parts. The regularities of changes in the characteristics of the elliptic slot antenna according to the variations of dielectric thickness are identified. Recommendations are given for the development of ultra-wideband antennas used in selecting the thickness of the dielectric. The results can be used to construct broadband antennas in telecommunication systems.*

Development and creation of antennas which correspond to contemporary market requirements assumes the usage of progressing instruments and methods which permit to carry out engineering calculations for identification of functionality and operating characteristics of the future device. The basic method for this has currently become computer simulation.

Using contemporary software packages any shape of antenna can be drawn easily on your computer and all kind of materials can be prescribed, and after that you will get the needed characteristics. Moreover antenna can be searched and optimized for specific conditions and requirements while changing its operating factors. After all, on the real antenna changing many operating factors is either very difficult or almost impossible.

One of the instruments that is allowed to carry out the designing of antennas, to calculate its performance attributes, to make a computer experiment which models conditions of the real world is the program High Frequency System Simulator (HFSS).The investigation of the dependence of the characteristics of the elliptical slot antenna on the change in thickness of the substrate was conducted in this program.

**Antenna construction.** The appearance of both side A and B elliptical slot antenna is demonstrated on figure 1 (A and B) correspondingly.

The antenna is accomplished on dielectric baseboard 4, on one side is metal elliptic resonator 1 with connected power line 2, on the other side all along the whole area of dielectric is metal screen 5 with elliptic slot 6. Antenna stimulation originates from discrete port 3 with impedance 50 Ohm.