Crop monitoring system based on earth image analysis to predict crop yields in fields

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Abstract

The paper discusses a methodology for monitoring agricultural crops based on the analysis of raster images obtained from aircraft. The method of determining the influence of atmospheric distortions on the analysis of crop conditions and harvest forecasting is considered. A method for determining the shading of a land area by clouds, as well as determining the presence of various substances in the soil, is described in detail. This is done by using edge pixel selection operators, which reduces the computational overhead of defining the area of cloud occlusion. The method is implemented based on the use of threshold processing, cellular automata technologies with Radon transform. Based on the obtained Radon projections, an analysis is made of the degree of shading of the agricultural area, as well as the state of the field in cloudy weather. In addition, the paper examines a method for analyzing the density of corn seedlings to predict future harvests. The method also uses theoretical principles of threshold processing of raster images, as well as the effective use of cellular technologies and Radon transformation, which makes it possible to determine the density of corn crops and identify weeds with high accuracy. The method does not require the use of high-quality raster images and performs calculations at high speed. The simplicity of the software implementation of the methods allows them to be implemented in simple computing devices.

Keywords

Raster image, atmospheric distortions, field shading, corn planting density, cellular automata, Radon transform

1. Introduction

In the life of every person there was a great desire to fly into the sky and look at the earth from above. The agricultural sector in people's lives is a necessary component of the survival and normal development of society. The development of information technology has made it possible to increase the productivity of the agricultural sector. The introduction of modern information technologies automates many processes in agriculture and also increases the yield based on the analysis of previous harvests. One of the widely used approaches is continuous monitoring of crops by analyzing images obtained from various aircraft. By analyzing images of crop fields, weather conditions are determined throughout the entire period of crop growth, and the condition of crops is determined and yields are predicted. By analyzing images of crop fields, agricultural workers can make informed decisions about fertilizing the soil, watering, and controlling pests and diseases. This approach uses images obtained from satellites or various aircraft from different altitudes. In this regard, high demands are placed on the quality of the obtained images, as well as on the methods of image processing to obtain high accuracy and reliability of the results.

To solve the tasks set, there are already methods that ensure high reliability of the analysis [1]. However, they are quite complex and require large computational resources. Therefore, there is a constant search for new, more advanced methods that can be used to solve many problems in

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processing images of crop fields. One of the approaches to the implementation of these methods are methods using cellular automata technologies [2], edge pixel analysis [3] and the Radon transform [4], which in such a combination make it possible to simplify the analysis and preliminary preparation of images, which increases the accuracy.

This paper discusses methods for analyzing and identifying atmospheric distortions that affect crop yields, as well as methods for assessing the condition of corn crops based on crop density analysis. To implement the proposed methods, technologies of cellular automata, threshold processing and Radon transform are used, as well as operators for selecting edge pixels on raster images.

2. Relative Works

The introduction of information technologies has made it possible to implement and use in the agricultural sector methods of remote sensing of agricultural crops [1], which are based on software and hardware systems of varying complexity. All of them use different models, which have different degrees of veracity [5 - 9]. Most of these systems use available data obtained over several years and also analyze data from systems with different models to forecast and analyze the yield. The described approaches also take into account the existing weather conditions and atmospheric states, the changes of which were carried out over long periods.

In the work [9] an analysis of works that use IoT for sensing agricultural crops, soil and microclimate is carried out. The types of technical means used to implement monitoring platforms are considered. Most of the works reviewed are aimed at the analysis of vegetation indices, pest identification and chemical therapy. However, little attention has been paid to methods for determining atmospheric distortions under different weather conditions, as well as automated assessment of crop density for forecasting the harvest in the current season.

The paper [10] also discusses various methods and means of satellite monitoring of agricultural crops. However, the paper notes the lack of quantitative, objective and reliable methods to ensure the reliability of harvest data. In particular, these studies do not fully take into account the actual dynamics of atmospheric distortions in a given period of time, and do not use clear indicators of crop density at an early stage to predict the yield.

In recent years, free access to satellite data has made it possible to obtain high-quality images of the earth's surface [11, 12]. There are cloud platforms that perform the necessary calculations and transformations of satellite images of the earth's surface.

Of all the earth's surface monitoring systems, a significant portion of them are aimed at analyzing the current state of crops and do not have the ability to forecast the harvest, and also do not monitor atmospheric distortions in real time in a limited mode. In addition, the systems do not fully analyze seedlings at the initial stage to predict the final yield of the field. In this regard, there is a need for an accurate analysis of the impact of weather changes, as they lead to stress in the growth of agricultural crops, which affects crop yields. To determine the cause that leads to stress, it is necessary to take a more detailed approach to the analysis of atmospheric distortions and take into account many indicators in a comprehensive manner, such as: the presence of clouds and the degree of field shading, as well as the percentage of humidity, illumination and others. At the same time, it is necessary that the monitoring system does not impose high demands on the quality of images of the earth's surface. In addition, the yield of many agricultural crops depends on the seeding density and plant density, as well as the presence of weeds, which requires automatic analysis of plant density and analysis of the presence of weeds that affect the quality of the crop.

3. Atmospheric distortion monitoring system for agricultural land surface image analysis

In modern conditions, when analyzing images of agricultural crops obtained from aircraft, problems often arise due to the influence of atmospheric distortions, such as clouds, light scattering, etc. The described processes affect the quality of the obtained images of the same surface under different weather conditions. The presence of various types of distortions reduces the ability to clearly analyze the image of fields with crops, which leads to false results when making decisions and forecasting the harvest. To improve the quality of field image analysis, there is a need to identify atmospheric distortions in satellite images or images obtained from various aircraft.

Existing methods do not provide high accuracy in determining the presence of clouds, which distort the analyzed areas of the field with crops with a certain degree of transparency. It is also difficult to determine the degree of distortion in high humidity, smoke and other distortions in a cloudless atmosphere of the earth.

To improve the accuracy of image analysis, the work uses a combination of methods for selecting the most informative pixels of a raster image using cellular automata technologies.

The method of monitoring atmospheric distortions is as follows.

At the initial stage, a color raster image of the earth's surface is formed using special means of video recording of the earth's surface located on aircraft (satellite, unmanned aerial vehicle, etc.). Examples of such images in Fig. 1 are shown.

Figure 1: Examples of images of fields recorded from aircraft.

Such images are generated using geographic information systems in agriculture. Electronic maps can be multi-layered, each layer of which can reflect the map of one field in different characteristics. For example, relief maps, NDVI vegetation, organic matter content map, iron, phosphorus and other content.

As a rule, each individual field on such maps is outlined in black (or another) color along the contour. The outline must not have gaps between pixels that belong to the given boundary of the land plot. Each pixel that belongs to the contour has properties that distinguish it from other pixels that do not belong to the contour. To do this, all pixels in the image are initially analyzed and a color that does not belong to any pixel is determined. This color (its code) is assigned to all pixels of the outline. As a rule, black color (code 0) is used.

The next step involves selecting the contour of a section of the earth's surface on a color image. Various isolation methods can be used, but the simplest is the method using cell technologies [2, 3].

The pixels belonging to the contour of the land plot are set in such a state that their codes are the same and these codes do not belong to other pixels of the image. For example, the codes of such pixels can take the value 5. The outer pixels of the image are encoded as 0. All other pixels are successively at each iteration step transitioned to a state that encodes 0 if one of the four neighboring pixels (von Neumann neighborhood) vertically (upper or lower neighboring pixels) and horizontally (left or right neighboring pixels) is not equal to 5. Fig. 2 shows examples of images after the first, tenth, fiftieth and sixty-fourth iteration steps. There are no changes in pixel codes inside the selected area, as shown in the last iteration step.

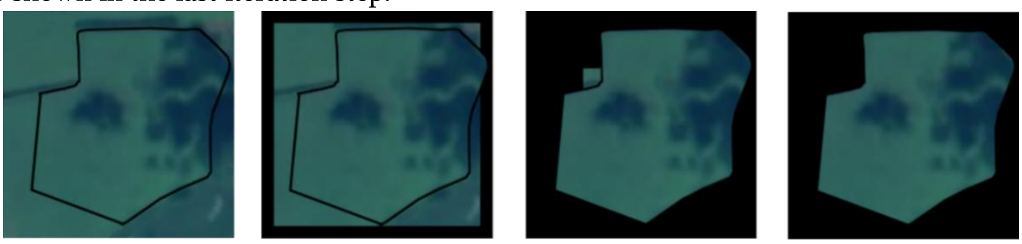

Figure 2: An example of highlighting a plot of land on a color raster image

As a result of this procedure, all pixels located outside the outline receive the code 0 and become background pixels, and pixels located inside the outline retain the original code.

To determine atmospheric distortions, a raster image is initially formed and analyzed in clear weather without clouds. An area of land is allocated in accordance with the method described above. The average value of the pixel codes located within the area is determined. Confidence interval values are set to identify groups of pixels that have the same color and brightness within the boundaries of the confidence intervals. To do this, determine the value of D according to the formula for each pixel of the selected area

$$D = I_{in} - S_{av}, \qquad (1)$$

were I_{in} – the value of the pixel code in the original image;

S_{av}, - average value for pixel codes of the selected area.

If $D < D_i$ (D_i - threshold value for the i-th group of pixels), for the corresponding pixel, then this pixel is assigned to the i-th group of pixels. An example of selecting such groups of pixels in Fig. 3 is shown.

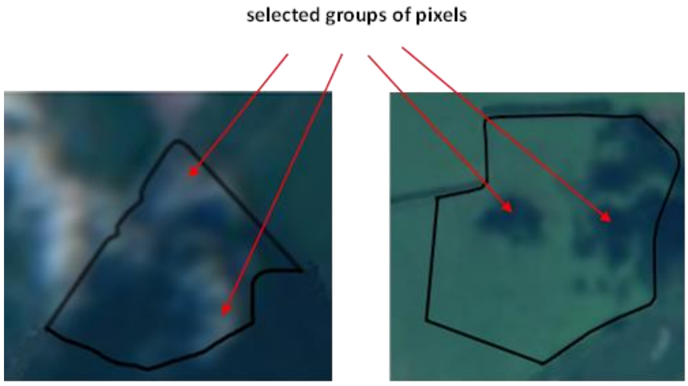

Figure 3: An example of selecting groups of pixels on an image of a selected area for different atmospheric distortions

To estimate the distortion in an image obtained in cloudy weather, the average value for the pixels of the selected area is calculated. A comparison is made of average values calculated from images obtained in clear and cloudy weather conditions. The magnitude of the deviation is used to determine the magnitude of distortion of the image of the earth's surface formed in cloudy weather.

To determine the degree of atmospheric distortion due to the presence of clouds, groups of pixels are identified from an image obtained in cloudy weather that differ from the pixel codes in an image obtained in clear weather without clouds. Figure 4 shows an example of selected groups of pixels that belong to clouds. On the left in Figure 4 are light clouds, and on the right are dark (not transparent) clouds. The selected areas are indicated by the red arrow. To determine the shadows from clouds on the earth's surface, another value D_i of the confidence interval is specified. The ratio of the pixel codes that belong to the cloud shadows in the image to the pixel codes of the unshaded area gives the percentage of cloud shading of the selected area of the earth's surface.

Using six projections for a binary image allows to identify shaded areas. In such an image, the code one is assigned to the pixels that belong to the shadows of the clouds, and all other pixels are assigned the code zero. To reduce the number of units, edge pixels are selected in the image using one of the edge pixel selection operators (for example, the Roberts operator, Prewitt, Sobel, etc.) [3]. The example shown in Fig. 5 shows the result of applying the Prewitt operator. Different operators produce edges of different thickness, but this does not affect the result. Based on the obtained images with highlighted edges, six Radon projections are formed at angles of 0^0, 30^0, 60^0, 90^0, 120^0 and 150^0 (Fig. 5). The resulting projections are compared with projections obtained in clear weather. The depth of pixel shading by the cloud in the image is determined from the selected edge pixels.

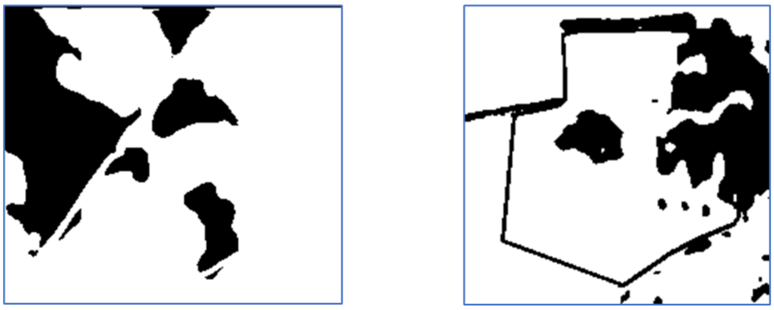

Figure 4: An example of highlighted groups of pixels indicating the presence of clouds

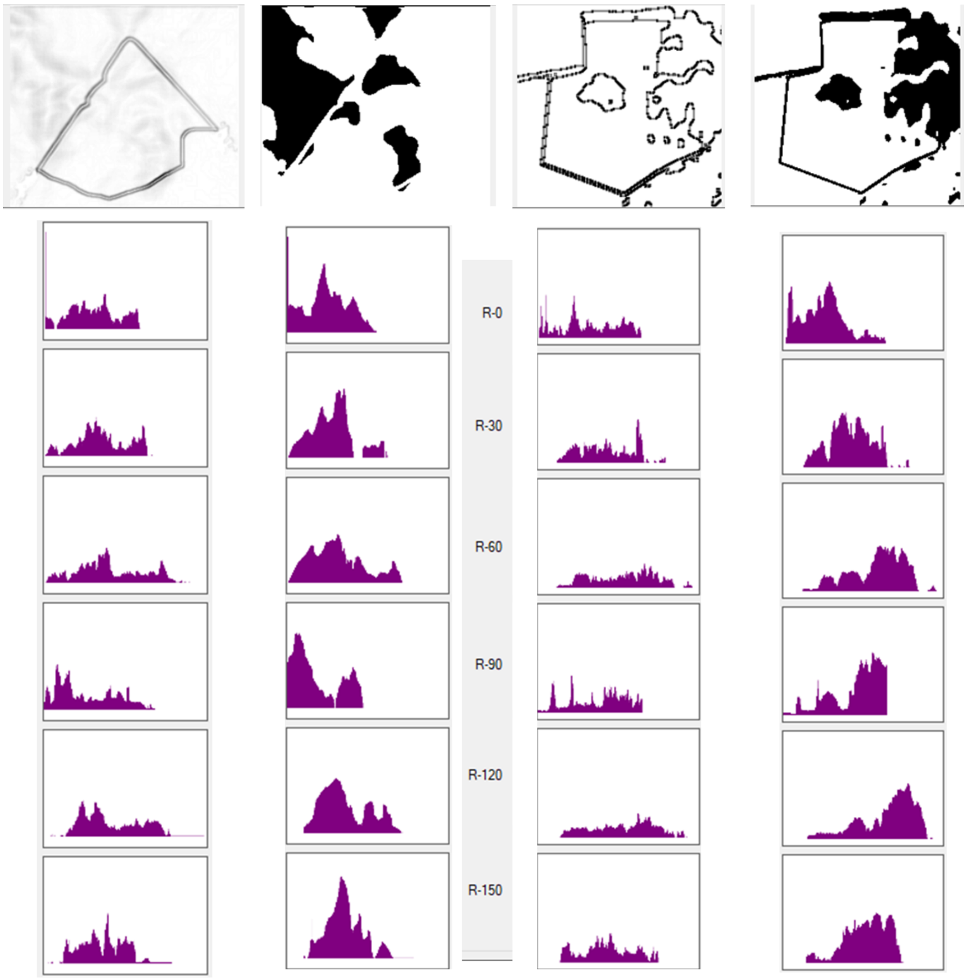

Figure 5: An example of the formation of six Radon projections at angles 0^0, 30^0, 60^0, 90^0, 120^0 and 150^0

The method allows you to select any area on a raster image without distorting the pixels located inside the area. This makes it possible to automatically assess the impact of weather changes on the quality of images of a section of the earth's surface, as well as determine the degree of shading of a control section of land. Using Radon projections allows us to determine with high accuracy the areas of land shaded by clouds, as well as to determine the degree of shading with the least computational effort.

4. Method for assessing the condition of corn crops based on the analysis of seedling density

Assessing the condition of corn crops is an important element in managing agricultural processes. One of the key parameters that influence the condition of crops and, accordingly, the yield, is the density of crops and plant growth. Insufficient or excessive density can lead to reduced yields through insufficient competition for resources between plants or through excessive shade and restriction of plant growth. The introduction of a system for assessing the condition of corn crops based on density analysis allows farmers to promptly identify and correct problems that will improve plant growth conditions.

There are a significant number of methods and software and hardware tools used to monitor plant crops, including analysis of the state of corn crops [13, 14]. However, the methods used do not always provide the desired analysis results, as they are not aimed at conducting a detailed analysis of the density of corn crops. The analysis is carried out by agricultural specialists in a semi-automatic mode without the use of expert systems. To improve the quality of crop condition analysis, this paper describes a method that combines threshold processing and cellular automata technologies, which automatically facilitates the work of specialists in analyzing crop density for predicting corn yields.

A raster RGB image is formed. Each color is displayed by one byte (8 bits). The image is formed by an unmanned aerial vehicle that flies over a corn field. The analysis is carried out at the early stages of corn germination, when the field is not very overgrown and there is a small number of weeds. In this case, the plants are sufficiently rooted and show effective growth. An example of such an image in Fig. 6 is shown.

Figure 6: Drone image of corn crop in early stages of growth

Since the corn seedlings in the image appear in shades of green, image thresholding is applied to highlight the plants present in the image. At the same time, weeds that also grow in the selected area are also identified. To select plants on a raster image, the following formula is used

$$P(t+1) = \begin{cases} 16777215, if \ \left(\frac{G}{R} < 1{,}2 \ and \ \frac{G}{B} < 1{,}2\right) \ or \ \frac{G}{B} < 1{,}22 \\ P(t), in \ other \ case \end{cases}, \quad (2)$$

were $P(t)$ - pixel code at time t (before thresholding);

R, G and B – codes of red, green and blue colors in the analyzed pixel, respectively.

The threshold values presented in the formula were obtained as a result of experimental analysis of images of corn crops. For plants of different colors, other threshold values may be used. For each plant variety, its own thresholds are selected experimentally. As a result of applying threshold processing to the presented example of a corn field plot, an image is formed in which only green plants are highlighted on a white background. An example of such an image in Fig. 7 is shown. The figure also shows highlighted dark green pixels representing shadows or dark areas of plants that do not affect the accuracy of further analysis. In fact, filtration is carried out to separate out green shoots.

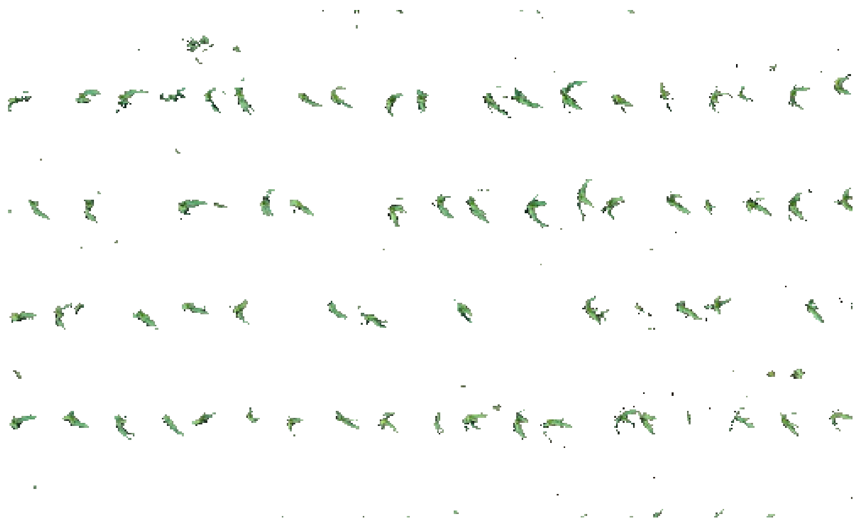

Figure 7: Image of corn crop after threshold treatment

The next step of processing is projection analysis. For this, Radon projections [4] are formed after the necessary affine transformations. The Radon projection used is the one that has a direction that coincides with the straight line of the corn rows. The image shown uses a Radon projection in the 0^0 direction. The result of the projection analysis for the example shown in Fig. 7 is the projection shown in Fig. 8.

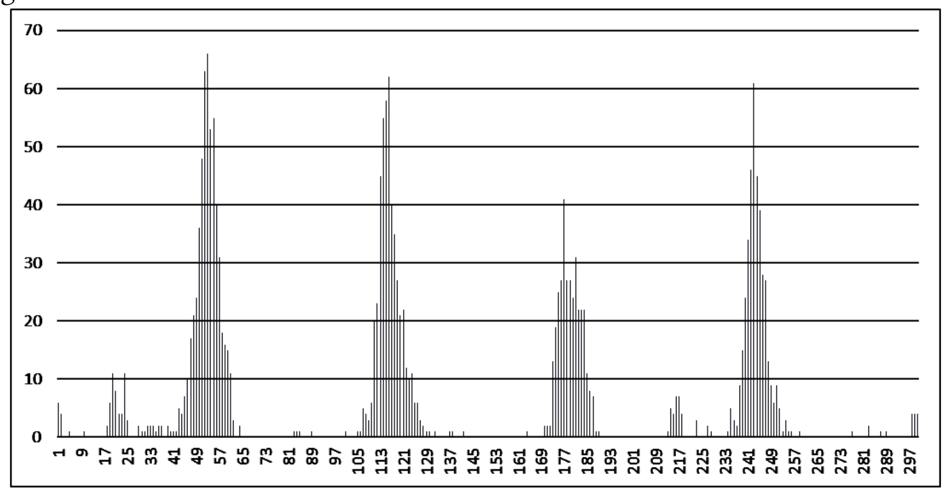

Figure 8: The result of forming the Radon projection in the 0^0 direction for the example shown in Fig. 7.

The projection analysis shows that there are four rows of corn in the analysis field. This is shown by the high amplitudes in Fig. 7. In Fig. 8 with projections there are also values with small amplitudes. Typically these small amplitudes indicate the presence of weeds. Threshold processing is used and a threshold is set that is slightly larger than the small spikes in the projection histogram. After this, those parts of the projections that display the corn rows remain. These projections show the spread width of the corn shoot leaves and their number in each row.

According to the horizontal projection analysis, the boundaries of each row are formed according to the width of each spike on the histogram. Each row is highlighted with a rectangular window and the image of each corn row is analyzed separately. An example image of a selected corn row in Fig. 9 is shown.

Figure 9: Example image of a highlighted corn row.

The resulting image clearly highlights each corn sprout. To count each corn plant in a row, a Radon projection is formed in the 90^0 direction. Such a histogram already has more peaks with larger amplitudes (Fig. 10).

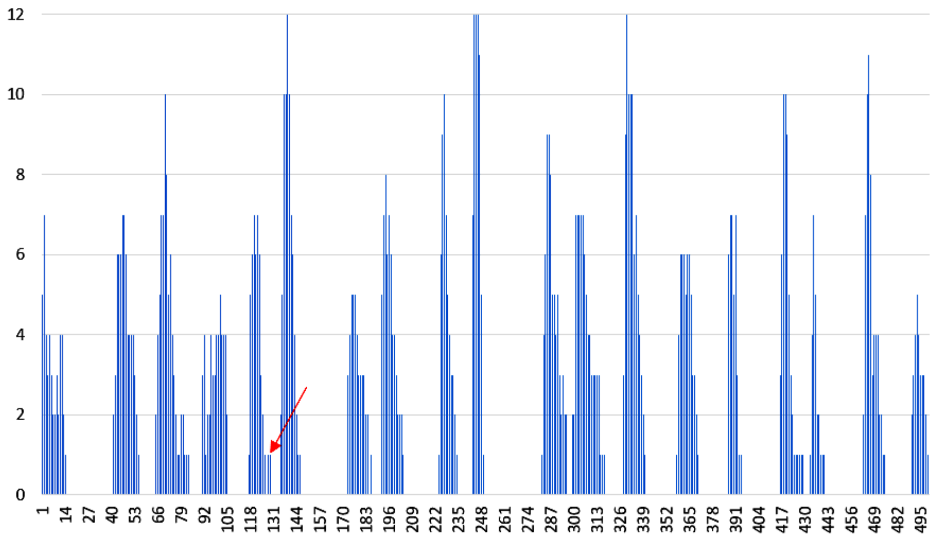

Figure 10: An example of generated Radon projections for one row of corn.

Radon projections are presented as a histogram, the height of each column of which determines the number of units in the corresponding column of the corn row image matrix. In Fig. 9, each corn plant is represented by a group of adjacent columns. However, there are small clusters (1 to 2 adjacent histogram peaks) with small amplitudes that indicate the presence of weeds between corn seedlings in the same corn row. In Fig. 9 such aggregates are indicated by a red arrow.

To remove such pixel clusters, cellular automata technologies are used, which also represent each corn sprout as a sequence of adjacent ones in a general sequence consisting of zeros and ones. To solve this problem, it was assumed that a corn sprout defines no less than three adjacent units. The evolution of elementary cellular automata is realized according to the following rule

$$x_2(t+1) = \begin{cases} 1, if\ \ (x_0(t) > 0\ and\ x_1(t) > 0\ and\ x_2(t) > 0)\ or \\ \qquad or\ (x_2(t) > 0\ and\ x_3(t) > 0\ and\ x_4(t) > 0)\ or \\ \qquad or\ (x_1(t) > 0\ and\ x_2(t) > 0\ and\ x_3(t) > 0) \\ 0, in\ other\ case \end{cases} . \tag{3}$$

As a result, small sets of pixels are removed, and a sequence of pulses is formed at the output, in which the width of each pulse can be different and corresponds to the size of the corn shoot (Fig. 11).

Figure 11: An example of a pulse sequence that determines the number of plants in a row.

Since the pulses are represented by different durations, there is a need to use additional transformations and solutions for their calculation. It is easier to count single pulses. Cellular automata technologies are also used to obtain such pulses. The following condition is realized.

$$x_1(t+1) = \begin{cases} 0, if\ \ x_0(t) = 1, x_1(t) = 1, x_2(t) = 0 \\ x_1(t), in\ other\ case \end{cases} . \tag{4}$$

The number of steps in the evolution of elementary cellular automata is determined by the number of neighboring units in a group that define one corn sprout. The result of such a transformation is a sequence of ones separated by a different number of zeros. Each individual unit represents one corn sprout. Such a sequence is easily transformed into a sequence of single pulses (Fig. 12), the number of which is equal to the number of corn shoots in a fixed area of the field.

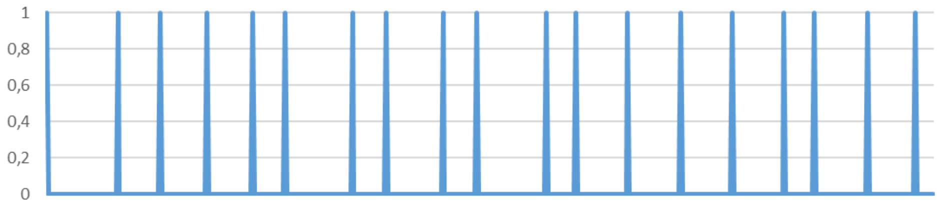

Figure 12: Sequence of single pulses after transformation.

In each selected section of the corn field image, the corn shoots are counted and the seeding density is determined, the value of which is used to predict the yield in the analyzed area. The method is suitable for analyzing the density of seedlings of other agricultural crops such as sunflower, peas, cotton, oats, cabbage and others.

5. Conclusion

The paper presents the results of combining edge pixel extraction methods, cellular automata technologies and Radon transform for efficient monitoring of the state of agricultural land areas recorded on raster images. The proposed methods make it possible to select any area in the image without distorting the codes of pixels located inside the area. This allowed for efficient analysis of atmospheric distortions during monitoring of the condition of a selected agricultural area on a raster image. Using edge detection operators and Radon projection analysis for a selected area, the degree of shading of an agricultural area by clouds and the impact on the quality of display of the area of the earth's surface under different weather conditions are determined. The use of the Radon transform made it possible to determine with high accuracy areas in fields shaded by clouds. The use of threshold processing in combination with cellular automata and Radon transform technologies allows us to estimate the yield of agricultural plants based on the analysis of crop density. Using the example of analyzing the density of corn crops, the effectiveness of the proposed method was proven, which provides 99% accuracy in automatically calculating the number of seedlings and determining the density of crops, which made it possible to predict the harvest with high accuracy. For the analysis of crop density of agricultural plants, high demands are not placed on image quality. The combination of the described methods automatically indicates the location of weeds, which makes it possible to analyze their impact on crop yield. The use of threshold processing implements additional functions of the system, which are aimed at analyzing the soil to determine the content of various chemicals, the amount of fertilizer in each section of the field and other components used in the agricultural sector.

In further studies, the authors plan to use analysis of the impact of weeds present in an image to predict crop yields.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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