The Image Analysis Algorithm for the Log Pile Photogrammetry Measurement

ARTEM KRUGLOV, YURIY CHIRYSHEV
Engineering School of Information Technologies, Telecommunications and Control Systems
Ural Federal University
Mira st., 32, Yekaterinburg, 620004
RUSSIAN FEDERATION
avkruglov@yandex.ru iurii.chiryshev@mail.ru

Abstract: - This paper is devoted to the investigation and development of the algorithm for the log pile photogrammetry measurement on the basis of abuts detection and calculation of their diameters. The algorithm of abuts contours detection and refinement relies on the modified radial symmetry object detection algorithm. The combination of the following methods is implemented at the further stages of the pile measurement algorithm: meanshift clustering, Delaunay triangulation, Boruvka's minimum spanning tree algorithm, watershed and Boykov-Kolmogorov graph cut algorithm. These methods were adapted to the specific of the given task. The testing of the resulting algorithm gives its TPR value at 96,2% which is much higher than other unsupervised training methods. The average error of the algorithm for the log pile photogrammetry measurement in comparison with manual measurement is less than 9.2%. It meets the requirements of the industry standards so the method of the log piles photogrammetry measurement using the developed algorithm can be successfully applied in the activity of forest enterprises.

Key-Words: - Log pile, Photogrammetry, Abut detection, Radial symmetry, Meanshift clustering, Graph cut, Watershed, Volume measurement

1 Introduction

The automatic detection of the static or dynamic target objects remains one of the urgent problems in the computer science. Thus a number of scientific researches referred to the radial symmetry object detection and related topics were observed in the first instance.

In the paper [1] it is suggested to construct the set of base attributes for the image of the directed edges (Canny detector) using the modified Viola-Jones algorithm with restricted Haar-like features space. Algorithm for the detection and isolation of the aerial objects based on the APCC background model parameters estimation through adaptive spatial filtration [4] shows insufficient efficiency in case of noise and low contrast of the targets. Method of searching the radial forms on the basis of swarm intelligence [6,7] uses the cost function to compare the candidate circle with the actual circle in the contour map of the input image, which based on the difference in their centers locations and radii lengths. Principal drawback of this approach is the necessity to know the number of required shapes in advance. Some methods rely on searching and grouping of the arcs. For example, in [11] describes a method for tracking in a video stream the objects comprising a plurality of concentric arcs, which based on the use of the structural tensor and the voting scheme in the space of arcs centers. Another method provides an ellipses detection using curve segments [12] - they checked pairwise for belonging to the same hypothesized ellipse and combined into one segment in case of matching. Method allows to detect ellipses under the bad light conditions, noise, overlapping yet false detection is occured rather frequently. Another hierarchical approach [13] consists in assembling of segments which potentially belongs to the same ellipse by condition of connectivity and curvature, grouping circular arcs belonging to the ellipse and estimating the matching between arcs and ellipse through RANSAC method. Possible disadvantage includes low efficiency for small sized objects. Detection with isophotes curvature analysis [14] implies the selection of the major pixels and classification them into subsets of the equal to the isophote curvature; the analysis of the hypothesized circles is carried out by voting strategy based on kernel density evaluation, and finally the algorithm is refined on the base of the linear error compensation. Method of circle detection by means of the gradient pair vectors [15] could be used to find circles which are brighter or darker than the background; firstly the gradient vectors of the circles in the image are calculated, then the oppositely directed pairs of vectors lying at the opposite points of the circle are searched and finally the circles from the candidates list of the previous step are selected. Method for ellipse detection by symmetry [16] relies on geometric properties: boundary points of the input image are separated into several images so that ellipses with different symmetry axis are in the different images, and symmetry procedure is applied to each image until five parameters (midpoint coordinates, angle, major and minor axes) would be obtained

The problem of the log abuts detection in the images was observed in several researches [49, 50, 52, 53], and some of them have found practical implementation as a part of the applicable measuring system [53]. Presented in this papers detection techniques could be divided into two categories. First group includes methods based on the machine learning. In [50] Herbon et al. describe the iterative algorithm for detection and segmentation which uses the descriptors of interest points based on histogram of oriented gradients (HOG) [46] in combination with Haar features and local binary patterns (LBP) [57] at the stage of the log abut detection. Gutzeit and Voskamp in [49] applied Viola-Jones algorithm means for implementation of the cascade of the classifiers where each of them is the assembly of weak classifiers; the features for the detection algorithm are the rectangular Haar ones.

Second group are the unsupervised training methods which used the assumptions of the form and size of logs [48, 53]. In general, these methods are based on the Hough transform [17-20] or its modifications and used to detect log abuts in the image in the form of circles or ellipses. Some of them are fail to meet the requirements of the mobile photogrammetry measurement due to the high computational complexity of the reported algorithms [21-24], low recognition rate [25,26] or high sensitivity to noise and other types of distortion [27-29], but in principal the methods of this group show high efficiency of the target object recognition.

2 Development of the algorithm for the log pile volume measurement

According to the modular paradigm [30] the image processing relies on a number of consequent levels from the lowest one connected with the pixel processing (noise filtering, histogram processing) to the highest one related to understanding of the image. Applying this approach to the development of the algorithm for the roundwood volume measurement is reduced to the following sequence of operations:

1) Object detection
2) Object isolation and classification
3) Segmentation
4) Geometric features determination
5) Volume measurement

2.1 Object detection

The detection stage involves the finding in the image all possible target objects which meet a number of criteria. The aim of the detection is to obtain the primary input data about measuring objects and select the necessary sets of features for further classification and segmentation. Analysis of the considerable number of the log pile images shows that the most log abuts have approximately circular form (Fig. 1).

It is necessary to underline the following aspects of the abut detection problem which must be taking into account during development of the detection algorithm:

– Abuts often have non-purely circular form (especially the bottom ones),

– Some wood kinds have concentric circles in the cutting (growth rings or medulla),

– Some abuts can be obstructed by other logs in a pile due to the rough stacking.

a b c

Fig. 1 – Examples of the log pile images

In the context of the given task the most appropriate detection method in terms of the computational cost and requirements to the possible distortions of the target objects is the one based on the evaluation of the fast radial symmetry transformation [32]. The principle of the method is in the following.

For each radius r the orientation O_r and magnitude M_r projection images are formed through the analysis of gradient g in each point p for which the coordinates of positive and negative points $p_{+ve}(p)$ and $p_{-ve}(p)$ are estimated as following:

$$p_{+ve}(p) = p + \mathrm{round}\left(\frac{g(p)}{\|g(p)\|} n\right)$$
$$p_{-ve}(p) = p - \mathrm{round}\left(\frac{g(p)}{\|g(p)\|} n\right) \quad (1)$$

In orientation and magnitude projection images the value of point p for each $p_{+ve}(p)$ is increased by 1 and $\|g(p)\|$ respectively whereas for the $p_{-ve}(p)$ the value is decreased by the same quantities. Thereby,

$$O_n(p_{+ve}(p)) = O_n(p_{+ve}(p)) + 1,$$
$$O_n(p_{-ve}(p)) = O_n(p_{-ve}(p)) - 1,$$
$$M_n(p_{+ve}(p)) = M_n(p_{+ve}(p)) + \|g(p)\|,$$
$$M_n(p_{-ve}(p)) = M_n(p_{-ve}(p)) - \|g(p)\|. \quad (2)$$

Accumulator F_r for the specific radius r is determined as the product of magnitude and orientation projection images:

$$F_r = M_r \cdot O_r^{\alpha} \quad (3)$$

where α – detector strictness which shows how well the target objects should correspond to the circle form.

As far as direction of the gradient vector has no odds for the given problem of log abuts detection, the accumulator F_r is determined as

$$F_r = \mathrm{sgn}(M_r) \cdot O_r^{\alpha} \quad (4)$$

The full transform is determined as sum of the symmetry contributions of the all considered radii

$$S = \sum_{r = r_{min}}^{r_{max}} S_r \quad (5)$$

where Sr is determined as convolution of accumulator F_r with Gaussian kernel A_r:

$$S_r = F_r * A_r \quad (6)$$

This method show high efficiency for the images with a priory known radii, low level of the form distortions and upon condition that the searching radii spread in a small range. The following hypothesis is used for assignment this range. Total amount of logs in a pile is in the range between 10 (otherwise it is easier to implement manual selection of the small batches) and 200 (bigger amount of abuts in the image cannot be measured due to their small relative size); the equivalent area of an abuts varies depending on the image, but its average value is about 30 per cent of the image. According to these limitations the range of the radii is determined according the following formulas:

$$R_{min} = \sqrt{\frac{A \cdot p}{\pi \cdot N_{max}}}$$
$$R_{max} = \sqrt{\frac{A \cdot p}{\pi \cdot N_{min}}} \quad (7)$$

where A – area of the image, p – the percentage of the image occupied by a pile, N_{min}, N_{max} – maximum and minimum amount of logs in a pile.

Such an approach allows to process the range of the most probable radii of abuts. The most part of the images from tested sample fits these assumptions; also they are specified in the user guide of the software for the mobile measurement of the pile volume as recommendations for taking pictures to obtain the best quality of the algorithm output.

The disadvantages of described method are the following:

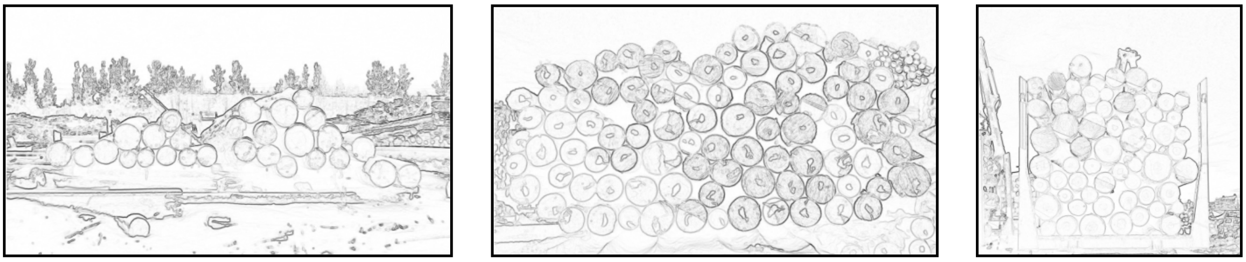
– The signal/noise ratio of the cumulative accumulator is significantly reduced with a large range of radii, resulting in complicacy of the potential circle centers detecting. It is related to the small fraction of the target objects contained in the detected sample of these radii;

– Computational complexity of the algorithm increases rapidly if detector strictness coefficient is not equal to 1, whereas α equal to 1 leads to the large amount of the false positive detection errors. It is better to define radial distortions for sampling the best candidates through comparative analysis of the algorithm output data in spite of set α coefficient from the parameters of the algorithm in an explicit form. This approach is more suitable for the problem of the abuts detecting where shapes of the target objects have significant deviations from the circle form.

– It is necessary to scan the output for each radius S_r after detecting of the potential circle centers in full transform output S to compare responses in detected points for radii refinement.

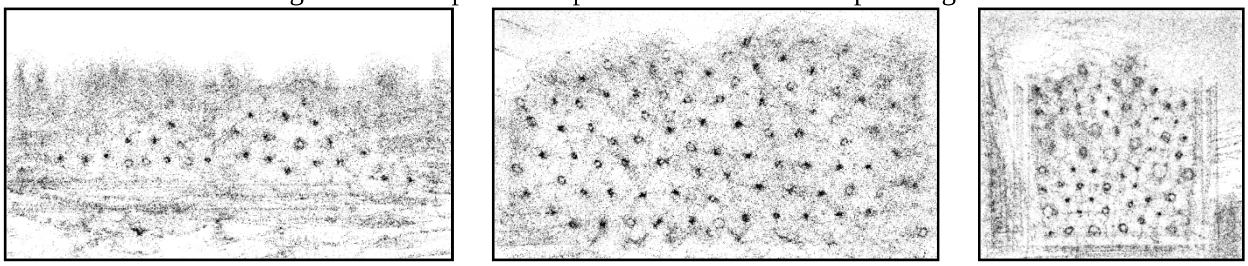
– Choosing the optimal threshold for analyzing the spikes of the full transform output for specific image.

Thus for the abuts detection task the modification of the radial symmetry object detection method was implemented in reliance on the above. The principle features of the offered transform are the following.



a b c

Fig. 2 – Sobel operator implementation to the sample images



a b c

Fig. 3 – Orientation projection images of the sample images

The magnitude projection image is not constructed as far as detector decisions are made on the basis of the modified orientation projection image analysis. First stage of the detection is the Sobel operator implementation for the boundary pixels recognition, which estimates the magnitude and the direction of gradient vector. The voting boundary pixels are the ones with the high value of the gradient magnitude. After that the gradient vector direction is estimated for each boundary pixel in order to calculate the center of circle of the radius R.

At second stage the search of the local maximum in the orientation projection is implemented. Originally the thresholding was applied to the projection image for parameter space analysis, however this approach does not involve the determination of the optimal threshold for the specific image. Also it is preferred for the local maximum points to be invariant to the image scale and consider the distortions of the target objects. Thus the orientation projection analysis was customized to the given task as following.

The algorithm splits the set of search radii into non-overlapping ranges to provide invariance to the image scale and target objects form distortions. Each range covers the specific scale interval and has its own size of the filter. The size of the filter is selected with considering the size of the target object and its permissible form distortions. It is evident that the greater radius of the object the more significant contribution into the local maximum of the orientation projection will be made by its boundary points. On the other hand, intensity variation near the local maximum in the accumulator increases with greater radius of the target object or its form distortions ratio relatively to the circle. Thus the projection of the greater radius should be scanned with aperture of the larger size. Thereby it was decided to calculate the specific size of the scanned aperture as function of search radius according to the formula

$$\mathrm{A_r} = \begin{cases} [\log_{10} \mathrm{Sq_r}] & \text{for odds} \\ [\log_{10} \mathrm{Sq_r}] + 1 & \text{otherwise} \end{cases} \tag{8}$$

where [] – integral part of a number, $\mathrm{Sq_r}$ - area of the circle of radius r.

The idea of the optimal threshold selection is that it can be evaluated from the result of the algorithm implementation to the image of the same size and brightness arrangement as the initial one but containing no radial symmetry objects. The random permutation of the rows and columns of the initial image was implemented, thereby the information about spatial location of the circular objects is hidden although intensity and direction of each pixel are stored.

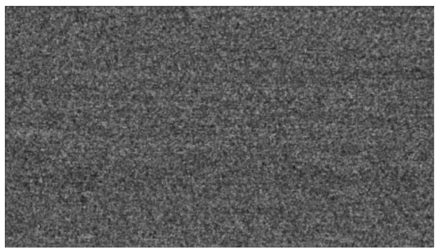


Fig. 4 – Visualization of the «noise» orientation projection with entropy of the image 2a

The value of the optimal threshold depends on initial image entropy, thereat the threshold for the segmentation of the initial image orientation projection can be selected as following:

$$T_r = \max(\widetilde{O}_r) + A_r^2 \quad (9)$$

where $\max(\widetilde{O}_r)$ –global maximum of the «noise» projection image scanning with the aperture A_r

A_r in the formula (9) can be interpreted as correction scale coefficient. The descriptor of the region of interest of specific radius r with the scale invariance is calculated as following

$$D_r(x,y) = O_r(x,y) - T_r \quad (10)$$

where $O_r(x,y)$ – local maximum with coordinates (x,y) in the projection image of radius r scanning with aperture A_r, T_r – optimal threshold for the radius r.

Thus the offered method solves two problems: the search of the target objects with radial symmetry and the computation of their descriptors with scale invariance. It means that the value of the interest point for orientation projection of radius r_1 is the same as the local maximum in accumulator of radius r_2 ($r_1 \neq r_2$). The greater the value of the descriptor (weight of the object) the more accurate the target object form matches the circle. This approach allows selection of the best candidates among the obtained objects. The result of the modified detection algorithm is shown in Fig. 5.

Inasmuch as cross-correlation of the near-by search radii has negative impact on the result (there are many overlapping circles in the Fig. 5) the filter function which considers the mutual overlapping of the circles according to their weights should be implemented. Also the log cuttings can have prominent medulla. In order to eliminate this effect another filtering function which analyzes coaxial circles (which assumed to be boundaries of log cutting and medulla) and gives priority to the one with greater radius is necessary. In the view of above the filtering algorithm is the following.

The meanshift clustering [32] is implemented to the output transform of the modified detection algorithm. The point is that for set of descriptors $\{d_i\}$ the density function is defined as

$$f(d) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left(\frac{d-d_i}{h}\right), \quad (11)$$

where h – aperture, it is equal to the minimum radius of the abut R_{min},

K(d) – kernel. In this case the Epanechnikov kernel [33], which has the radial symmetry, is implemented

$$K(d) = \begin{cases} 1-d, & 0 < d < 1 \\ 0, & d > 1 \end{cases} \quad (12)$$

The idea is to shift the points in the direction of the local density increasing. In order to estimate this shift the gradient $\nabla f(d)$ is applied to the density function:

$$\nabla f(d) = \frac{2}{nh^4}\sum_{i=1}^{n} g\left(\left\|\frac{d-d_i}{h}\right\|^2\right) \cdot m(d), \quad (13)$$

where $g(\|d\|^2) = -K'(\|d\|^2)$,

$m(d)$ – meanshift vector.

$$m(d) = \left(\frac{\sum_{i=1}^{n} d_i g\left(\left\|\frac{d-d_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{d-d_i}{h}\right\|^2\right)}\right) - d \quad (14)$$

Vector $m(d)$ is always directed toward the maximum increasing of the density. Descriptors $\{d_i\}$ clustering procedure is the following:

a) Calculating the meanshift vector for each descriptor d_i,

b) Shift by $d_i \rightarrow d_i + m(d_i)$,

c) New iteration until the stable equilibrium of mass center is reached ($m(d_i) \rightarrow 0$),

d) Descriptors with the same mass center compose cluster.

The average weighted radius is calculated for each cluster:

$$r_{cp} = \frac{\sum_{i=1}^{n} r_i \cdot \omega_i}{\sum \omega_i}, \quad (15)$$

where n – cluster cardinality,

ω_i- weight function:

$$\omega_i = l_{r_i} \cdot n_{r_i}, \quad (16)$$

where l_{r_i} – radius, n_{r_i} – number of radius of given length in the cluster.

Result of the filtration is shown in Fig. 6.

2.2 Clustering

Clustering solves the problem of grouping the set of the objects obtained at the previous stage into the disjoint subsets of the target and nontarget objects. For the problem of the pile volume measurement the aim is to divide the detected objects into two subsets – «pile» and «non-pile». In such a way the image regions which are selected at the detection stage but not related to the target objects will be excluded before the segmentation and measuring.

Firstly it is necessary to construct the feature set and metrics based on the purpose of the clustering. The useful assumption is that the logs in a pile displayed in a feature space as a closely adjacent points. It is evident that the closer objects to each other the higher probability of their belonging to the same group. Thus the geometrical similarity metric (log density) was introduced to solve the clustering problem. This metric defines weather the log belongs to the pile or not. Among the existing clustering methods [34] – statistical, hierarchical, graph – the last ones were selected due to their clarity and simplicity.

a b c

Fig. 5 – Implementation of the modified detection algorithm

a b c

Fig. 6 – Result of the filtering

a b c

Fig. 7 – Structure of the pile determined by the graph algorithm

The following algorithm is implemented to the set of the detected objects:

1. Iterative Delaunay triangulation [35] with dynamic caching [36],
2. Finding the minimum spanning tree through Borůvka's algorithm [37];
3. Cut of the tree along edges until the condition (17) is reached.

$$\max_{(v,u)\in E} c(v,u) < 2 \cdot \max(r_{cp}), \qquad (17)$$

where E – set of the graph edges, $c(v,u)$ – weight of the edge (its length in this case), r_{cp} – the average weighted radius (15)

3. The different criteria for the inclusion of the obtained connected components $G(V_i)$ into the final sample $G(V)$ can be implemented. For example the criterion of the unicity of the pile in the image:

$$G(V) = \max|G(V_i)| \qquad (18)$$

After the primary testing the algorithm is amended to implement the criterion of the excluding from the consideration groups of less than five logs:

$$G(V) = \cup\, G(V_i): |G(V_i)| \geq 5 \qquad (19)$$

The result of the clustering is shown in Fig. 7.

2.3 Segmentation

Segmentation is carried out to refine the contour of each abut and to extract feature set for further pile volume measurement. Literature analysis [38-40] has shown that for the given task the most preferable methods according to the quality of segmentation are the ones based on the graph theory [41, 42]. In these methods the image is represented as a graph and it is partitioned by the cut which is minimized some energy determined by the purpose of the segmentation. The point of the minimum s-t cut of the graph is to split the set of graph nodes $G(V)$ into to subsets $G(S)$ и (T) $(G(S) \cup G(T) = G(V), G(S) \cap G(T) = \emptyset)$, where $s \in G(S), t \in G(T)$, in such a way that sum of the cut-edge weights is minimum:

$$\sum_{\substack{(i,j)\in G(E) \\ j\in G(S), j\in T}} c(i,j) \rightarrow \min \qquad (20)$$

where $c(i,j)$ – weight of the edge which corresponds with the brightness of the pixels i and j of the image.

The segmentation algorithm relies on the combination of two methods: marker-based watershed [43] and Boykov-Kolmogorov algorithm of the minimum s-t graph cut [44]. Watershed algorithm is used to specify the regions where abuts are located. Its output is a set of image regions containing the detected radial symmetry objects (Fig. 8,a-c). At that an approximate boundary of each object is known as far as it is the average weighted radius r_{cp} that should be rectified.

Using the obtained input data it is possible The automatic determination of the terminal areas (S) and (T) for the source and sink nodes in min-cut/max-flow algorithm is possible using the previously received data:

$$(S)_i \sim \left\{ s_i | s_i < \sqrt{\left(\frac{r_{cp_i}}{2}\right)^2 - d_i^2} \right\}, \quad (T)_i \sim \left\{ t_i | t_i > \sqrt{\left(\frac{3 \cdot r_{cp_i}}{2}\right)^2 - d_i^2} \right\} \tag{21}$$

Put this another way the area for source node selecting within less than $1/2 \cdot r_{cp_i}$ whereas the sink node area is farther than $3/2 \cdot r_{cp_i}$ from mass center d_i. The conclusive region corresponding with abut in the image is determined by the combination of the watershed and s-t cut outputs:

$$G(V)_i = G(S)_i \cap W_i \tag{22}$$

where $G(V)_i$ – region of the abut i, $G(S)_i$ – region of the abut i according to the s-t cut output, W_i – watershed basin containing marker i.

Output of the algorithm is shown in Fig. 8,d-f. In the conclusive image each pixel has label of the specific object or background; pixels of the same color are attributed to the same abut.

2.3 Log pile volume measurement

After that the set of the labelled regions is obtained it is necessary to determine their properties which will be used for log volume measurement and the pile model building. The following geometric properties of the region are calculated to provide the log volume measurement: area (23), mass center (24), length and orientation of the semi-axis of the equivalent ellipse. The mathematical apparatus of the mass moment of inertia [50] is used to calculate the mentioned properties.

$$A = \sum\sum I(x,y) \tag{23}$$

$$\bar{x} = \frac{\sum\sum x \cdot I(x,y)}{A}, \quad \bar{y} = \frac{\sum\sum y \cdot I(x,y)}{A} \tag{24}$$

Semi-axles orientation determines by the eigenvectors of the covariance matrix, and their length determines by the eigenvalues..

$$cov = \begin{pmatrix} m_{20} & m_{11} \\ m_{11} & m_{02} \end{pmatrix} \tag{25}$$

$$\theta = \frac{1}{2} \operatorname{atan}\left(\frac{2m_{11}}{m_{20} - m_{02}}\right) \tag{26}$$

where central moment m_{ij} determines as following:

$$m_{ij} = \sum (x - \bar{x})^i (y - \bar{y})^j I(x,y) \tag{27}$$

The pile volume measurement is based on the mathematical model of the pile where it determines as a set of cone frustums which bases are characterized by equivalent ellipses. Diameter of the abut is calculated as arithmetic mean of major and minor axis of an ellipse

$$d = \frac{d_1 + d_2}{2} \tag{28}$$

The volume of the pile is calculated as a sum of its log volumes:

$$V = \sum_{i=0}^{n} V_i \tag{29}$$

The volume of the separate log is measured according to the requirements and rules of specific country on the basis abuts diameters and length of a log . In Russian Federation the measuring of logs is carried out according to the methods from GOST R552117-2003.

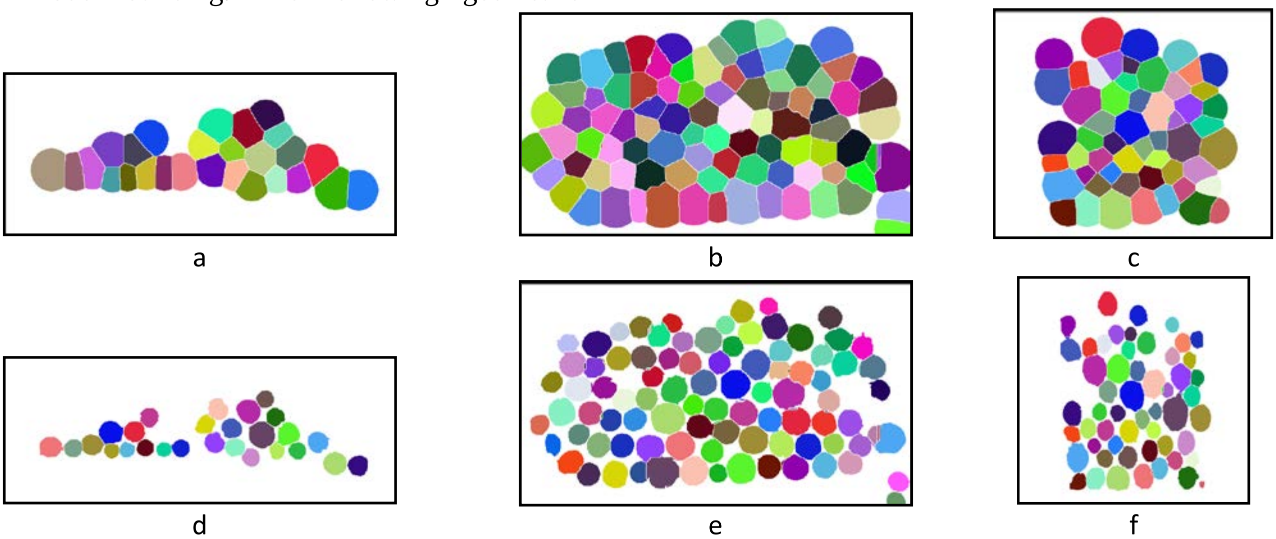


Fig. 8 – Abuts segmentation algorithm: a-c) watershed; d-f) combination with s-t cut

The convenient method for the mobile photogrammetry measurement of the pile volume is Frustum Cone Method. It means the volume measurement by the top diameter d, butt diameter D and log length L according to the frustum cone formula:

$$V = \frac{3{,}1416 \cdot L(d^2 + D^2 + d \cdot D)}{12 \cdot 10000} \quad (30)$$

3 Testing

The testing of the algorithm was carried out on the tablet Samsung Galaxy Tab 3 GT0P5210 16 Gb 10,1”. Requirements to the picture taking are the following: camera is parallel to the abuts plane, pile is located at the center of the frame with space between the frame edge and the nearest abut. There were 632 measurement of the piles under the different conditions during the algorithm testing:

– In stack and in the log truck,

– Stacked oriented (by tops or butts) to the camera or randomized,

– Different weather conditions (snow, solar etc.).

Results of the testing show that the offered algorithm based on the modified radial symmetry detection method reaches higher performance in comparison with methods based on linear classifiers (SVM+HOG, accuracy 77.9% [50]) and weak classifiers cascades (AdaBoost+Haar, accuracy 95.1% at the false positive rate 4.9·10-3). Also the offered algorithm is outperformed the methods based on Hough transformation (CHT+LCM, accuracy 90.8%) (see Table 1).

Table 1 – Comparison of the methods

Method	TPR (σTPR), %	FPR
LBP [50]	95,8(3,7)	$2{,}4 \cdot 10^{-3}$
HOG [50]	77,9(10)	-
LBP+HOG [50]	96,0(3,1)	$2{,}4 \cdot 10^{-3}$
HAAR [50]	95,1(3,8)	$4{,}9 \cdot 10^{-3}$
HAAR+HOG [50]	96,0(3,5)	$4{,}9 \cdot 10^{-3}$
LBP+HAAR+HOG [50]	98,4(2,1)	$6{,}6 \cdot 10^{-3}$
CHT+LCM[48]	90,8(9,4)	-
CHT[48]	84,8(11,6)	-
LCM[48]	89,7(9,8)	-
Our	96,2(4,1)	-

On the other hand the algorithm is inferior to the methods described in [50] when the last are strengthened by the combined classifiers and considered the abuts textural information (LBP+HAAR+HOG, accuracy 98.4% at the false positive rate 6.6·10-3). In spite of high rate of TPR this method has much higher computational complexity which is sensitive for its implementation for mobile devices.

4 Conclusion

The development of the pile volume measurement algorithm with modified method of the radial symmetry objects detection is described within this paper. Approbation of the algorithm was performed in the logging enterprise under the manufacturing conditions and shown the high efficiency of the offered measurement technique. According to the testing results the average error of the algorithm for the log pile photogrammetry measurement is less than 9.2% that is the best performance in comparison with Hough-based methods [48] (see Table 2).

Table 2 – Algorithm performance

Method	average error %
CHT+LCM[48]	14,22 (13,03)
CHT[48]	29,06 (19,13)
LCM[48]	21,42 (17,92)
Our	9,2 (8,9)

Industry standards establish the maximum volume measurement error for the round timber at the level of ±12%. Thus, a method of the log piles photogrammetry measurement using the developed algorithm can be successfully applied in the activity of forest enterprises.

The developed algorithm is implemented in the software for the mobile measurement of the pile volume «FoRest». This software is successfully used at the logging enterprises of the Ural Federal District at the moment.

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