Quantitative analysis of marker-based watershed image segmentation

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A methodology is proposed by combining the application of markers along with watershed transformation and thresholding for image segmentation. Use of the traditional watershed algorithm is widespread because of its advantage of being able to produce a complete division of the image. However, its drawbacks include over-segmentation and noise sensitivity. Therefore, the marker-based watershed segmentation is proposed here to overcome these effects. First, the original image is preprocessed by filtering techniques in order to smoothen it. Secondly, the foreground objects are marked. Then, the background markers are computed. Finally, the marked image is transformed through watershed transformation. The area is computed for the segmented objects in the image. It has been proved that this method reduces the error percentage.

Keywords: Gradient magnitude, image segmentation, markers, morphology, watershed.

IN the field of research and application, the areas of interest are those with unique characteristics[1]. Image segmentation is a branch of image processing where a specific region of interest with distinguishable property is extracted. Generally, it is the process of isolating objects in the image from the background, i.e. partitioning the image into disjoint regions such that each region is homogeneous with respect to some property, such as texture or grey value[2,3]. The separation and extraction of such specific regions are important for further identification and analysis. Image segmentation is extensively used in practice nowadays. There are many techniques for image segmentation and they are generally application-specific, depending upon imaging modality and based on the region of interest to be studied. A combination of various features can also be used in the segmentation process[4].

The watershed transformation in greyscale mathematical morphology was initially proposed by Digabel and Lantuéjoul[5] as well as Bencher and Meyer[6], and improved later by Beucher and Lantuéjoul[7]. In comparison with the traditional image segmentation, the watershed segmentation overcomes a few drawbacks[8] and is therefore gaining popularity in recent years. Generally, the watershed algorithm deals with two different approaches: immersion approach and toboggan approach. The former approach is also called flooding[9]. The name 'toboggan' is used because of its similarity in riding a sled downhill to the bottom of a basin[9].

In this study, the marker-based watershed algorithm and thresholding is used to address the issue of over-segmentation. Quantitative analysis of watershed segmentation is also performed.

Marker-based watershed segmentation

The watershed algorithm is a region-based image segmentation technique in which mathematical morphology is used. It is capable of obtaining the one-pixel width, consecutive and accurate boundary. The watershed algorithm considers the image to be a geographical surface[10], where the grey values are taken as the elevation from the ground surface and water flow is initiated either by immersion approach or toboggan approach.

The disadvantage of the traditional watershed segmentation is the presence of dark texture and dark noise, which give rise to many pseudo-local minima that may produce the corresponding pseudo-water basins. Thus, this method is sensitive to the noise present in the image and leads to over-segmentation.

In order to address the over-segmentation issue caused by the traditional watershed algorithm, an improved method called marker-controlled watershed segmentation for low-level segmentation[11] and marker-based watershed is introduced, which is capable of efficient image segmentation[12].

Mathematical morphology

Generally, mathematical morphology denotes a branch of biology which deals with various forms and structures of plants and animals. In the field of computer vision, it is a tool that is used to extract image components that are useful in the representation and description of the object shape. The image needs to be transformed into a better form which makes image analysis and the pattern recognition process much more effective.

Morphological operators

Here we discuss some of the morphological tools used along with the algorithm[13]. The basic operations of

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morphology are erosion and dilation. Two sets of erosion and dilation are used where the first one is performed with a flat structuring element and the second one with geodesic transforms.

If $f(x)$ denotes an input signal where M_n is a flat structuring element or window of size n, then the erosion and dilation by structuring element M_n are given by

$$\text{Erosion: } \varepsilon_n(f)(x) = \text{Min}\{f(x+y), y \in M_n\}. \tag{1}$$

$$\text{Dilation: } \delta_n(f)(x) = \text{Max}\{f(x-y), y \in M_n\}. \tag{2}$$

Geodesic dilation and erosion of arbitrary size are defined by iterations. For example, the geodesic dilation or erosion of infinite size, which is also known as reconstruction by dilation or by erosion is given by

Reconstruction by dilation:

$$\gamma_{(\text{rec})}(f,r) = \delta_{(\infty)}(f,r) = \ldots\delta_{(1)}(\ldots\delta_{(1)}(f,r)\ldots,r). \tag{3}$$

Reconstruction by erosion:

$$\varphi_{(\text{rec})}(f,r) = \varepsilon_{(\infty)}(f,r) = \ldots\varepsilon_{(1)}(\ldots\varepsilon_{(1)}(f,r)\ldots,r). \tag{4}$$

The basic dilation of size one defines the notion of neighbourhood and connectivity. The usage of queues avoids the iteration process and results in faster response for the reconstruction process.

Elementary erosions and dilations allow us to define the morphological filters.

Morphological opening:

$$\gamma_n(f) = \delta_n(\varepsilon_n(f)), \text{ i.e.; } \gamma_n = \delta_n\varepsilon_n. \tag{5}$$

Morphological closing:

$$\varphi_n(f) = \varepsilon_n(\delta_n(f)), \text{ i.e.; } \varphi_n = \varepsilon_n\delta_n. \tag{6}$$

Morphological opening or closing simplifies the original image by removing the dark (bright) components that do not fit in the structuring element. In order to deal with both the bright and dark elements, a close–open or open–close is used.

Opening (closing) by reconstruction of erosion (dilation)

First, the bright components that are smaller than the structuring element are simplified by the process of erosion. Then the reconstruction process restores the contour of the components that have been removed by means of erosion. The image obtained with the filter through reconstruction is a good starting point in the segmentation process.

Methodology of marker-based watershed algorithm

The proposed marker-based watershed algorithm is a step-by-step process. In the first step the image to be segmented is acquired and converted into greyscale. A structuring element or probe element is defined based on the input image. The foreground and background markers are computed. Finally, the watershed algorithm is visualized. Figure 1 is a flow chart of the proposed methodology.

Image preprocessing

The preprocessing step is done in order to rectify the unwanted noise characteristics of an image which are added to it during the process of image acquisition, i.e. it is essential in order to remove the artifacts[14]. The preprocessing methods performed are contrast enhancement and filtering. The geometrical distortions, which occur during image formation are restored. The gradient magnitude is one of the best parameters chosen as a segmentation function, because the value of the pixels along the edges would be high whereas other regions would correspond to lower values[15]. Generally, the Sobel operator is used for edge detection, but when Sobel is applied along with the watershed transform it results in over-segmentation.

Intensity adjustment is done by mapping the intensity of the pixels present in the image to a new range of values. In the spatial domain, the operator acts directly on the pixels of the image. The image is enhanced, limiting the intensity value of the pixels in the upper bound and lower bound by 1% during the transformation. Using the unsharp masking, the image is sharpened. The contrast can also be adjusted through automatic contrast adjustment

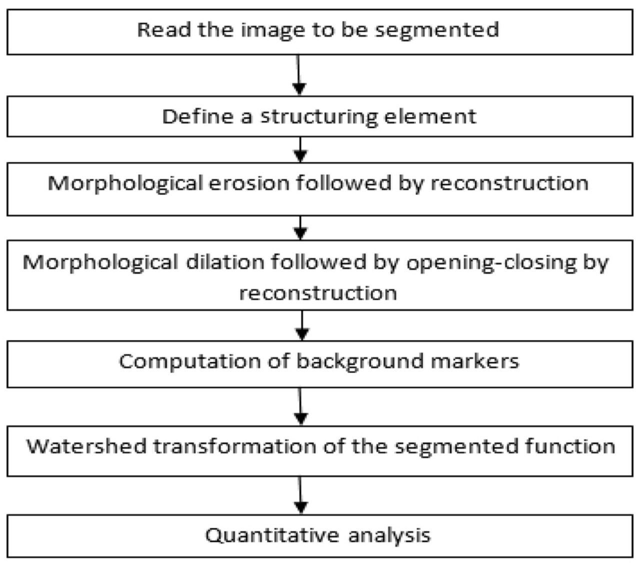

Figure 1. Framework of the marker-based watershed segmentation.

technique. The filtering process is applied to differentiate the foreground and background objects. Next, a set of mathematical operations is performed as part of the preprocessing operation. Selecting a proper preprocessing algorithm along with the watershed transform results in more accurate segmentation. In this study, open–close by reconstruction is used to preprocess the image before the watershed transform is applied.

Structuring element

A simple, predefined structure that is used to probe an image is called a probe or disc element or the structuring element. In terms of mathematical morphology, a structuring element is a structure or a shape which is utilized to interact along with an image, to check how the probe fits or misses the shape in the image. Mathematical morphology uses the structuring elements in order to measure and distill the corresponding shape of an image to reduce the image data, to keep to the basic structure and attain the objective of the analysis[12]. Segmentation through the watershed algorithm not only depends on the markers, but also on the marking function[16]. A good marking function should be capable of synthesizing the physical characteristics of the objects to be segmented. It must also have different markers and catchment basins characterizing the desired objects. The markers can also be selected by AWMS (adaptive marker-controlled watershed segmentation) algorithm[17].

The structuring element is defined based on the geometry of the foreground object. An image is generally a representation of pixels. The structuring element can be of different shapes and sizes. Selection of the probe is a key factor in the morphological process. Here, we use a disc-shaped structuring element, which is flat in nature. Since the shape of the coin resembles a circle, a disk-shaped structuring element is used. The disc element for mask is defined by decomposition mechanism. Then the disc is defined for a particular radius based on the image to which the probe needs to be created. Coins generally vary between 6 and 9 pixels in radius. In this study, a pixel value of 8 is chosen as the radius of the disk, such that the coin and probe would map onto each other.

Morphological erosion

The process of erosion is performed after the opening filter is applied to the greyscale image. Opening is nothing but erosion followed by a dilation, whereas opening-by-reconstruction is erosion followed by morphological reconstruction. Consider two images A and B, where A is being eroded by B.

The erosion operation can be defined as

$$A \Theta B = \{z \mid B_z \cap A_c \neq \phi\}, \tag{7}$$

where ϕ is the empty set, A_c is the image to be eroded and B_z is the structuring element.

The greyscale erosion with a flat, disk-shaped structuring element will generally darken the image. The bright regions that are surrounded by dark regions shrink in size, while the dark regions surrounded by bright regions grow in size. Small bright spots in the image will disappear since they are eroded due to the surrounding intensity and the small dark spots will become larger spots.

Morphological reconstruction

Morphological reconstruction is a part of the set of image operators referred to as geodesic. The eroded image needs to be reconstructed to extract the connected components of the mask which are marked. The advantage of this method is that it can filter out the connected components which are not contained in the disc, while entirely preserving the other components. Reconstruction is a useful operator in mathematical morphology. Morphological reconstruction is effective to extract marked objects, detect or remove the objects that touch the image boundary and filter out spurious high or low points[18].

In case of binary image, the connected component for two images are defined on the same discrete domain D, such that $J \subseteq I$. In mapping terms: $\forall p \in D$, $J(p) = 1$; $I(p) = 1$, where J is the image to be processed, while, I is the mask. Let $I_1, I_2, I_3, \ldots, I_n$ be the connected components of I. The reconstruction $\rho_1(J)$ of a mask of the image is the union of the connected components of the image which contain at least a pixel of J

$$\rho_1(J) = \bigcup_{J \cap I_{k \neq \phi}} I_k. \tag{8}$$

Let I and J be the eroded image and the real image respectively. Both the greyscale images are defined in the same domain taking their values in the discrete set $\{0, 1, 2, \ldots, N-1\}$, such that $J \leq I$, i.e. for every pixel $J(p) \leq I(p)$. The greyscale reconstruction $\rho_1(J)$ of I from J is given by

$$\forall p \in D_1;$$
$$\rho_1(J)(p) = \max\{k \in [0, N-1] \mid p \in \rho_{TK(1)}(Tk_{(J)})\}. \tag{9}$$

Morphological dilation

For the process of opening by reconstruction, the reconstructed image needs to be dilated. Dilation is an operation that increases the thickness of the object present in the image. Mathematically, dilation of A by B is defined as

$$A \oplus B = \{z \mid B_z \cap A_c \neq \phi\}, \tag{10}$$

where ϕ is the empty set, A_z the image to be dilated and B_z is the structuring element. Dilation operation is commutative in nature, i.e. $A \oplus B = B \oplus A$. The basic effect of the operator is that it gradually enlarges the boundary regions of the foreground pixels. The advantage of this is that the small bright spots will become larger spots, whereas small dark spots will disappear since the dark spots will be filled by intensity value of the surrounding pixels[19].

Opening–closing by reconstruction

The morphological reconstruction by opening–closing can be extended from binary image to greyscale image[20]. Closing–opening by reconstruction is the process of dilation applied onto the reconstructed eroded image. This involves the process of erosion, dilation and reconstruction. In order to perform opening–closing by reconstruction, the eroded and dilated image must be complemented. The regional maxima of the reconstructed image is found. In order to interpret the result, the foreground marker image is superimposed on the original image and the regional maxima is computed and compared. However, some of the shadowed and occluded objects are not marked, i.e. these objects will not be segmented properly in resulting image, so the edges of the marker must be cleaned and then the marker image must be shrunk[21]. Smaller objects existing in the image are removed and then the maxima image is generated.

Computation of background marker

The opening–closing reconstructed image is binarized in order to perform thresholding of the image. After this the background pixels are in black, but it is not ideal for the background markers to be close to the edges of the objects that are to be segmented. To overcome this, we perform watershed of the distance transform.

The Euclidean distance transform is computed where the distance transform assigns a number, i.e. the distance between that particular pixel and the nearest non-zero pixel of the image. The Euclidean distance between two pixels $A(x_1, y_1)$ and $B(x_2, y_2)$ is mathematically computed by[22]

$$\Delta(A,B) = \left(\sum_{i=1}^{k} | A_i - B_i |^p\right)^{1/p}, \tag{11}$$

where A and B are k-tuples and A_i and B_i are the ith coordinate of x and y, and $1 \le p \le \alpha$.

Watershed transform

The watershed line is a segmenting tool. The topographical distance is computed by the Euclidean algorithm between two pixels considering the shortest path. Simply, the equation can be redefined as $\mathrm{TD}(A, B) = f(q) - f(p)$. In other cases, we have $\mathrm{TD}(A, B) > f(q) - f(p)$, where TD corresponds to the topographical distance. Hence the lines of the steepest slope are the geodesics of the topographic distance function. The catchment basin of the regional minima is a set of points that are closer to it.

The watershed line is a function, i.e. the set of points of the function f which do not belong to any other catchment basin

$$W_{\mathrm{sh}}(f) = s(f) \cap [\bigcup_i (\mathrm{CB}(m_i))]^c, \tag{12}$$

where $s(f)$ is the support to the function f and $\mathrm{CB}(m_i)$ is the catchment basin with the regional minima m_i.

Generally, to overcome over-segmentation issue the background is made thinner by finding the SKIZ, i.e. skeleton by influence zones of the foreground image. SKIZ is computed by performing the distance transformation over the foreground image.

Mathematically, the geodesic distance zone ($iz_A(B_i)$) is given by

$$iz_A(B_i) = \{a \in A, \forall j \in [1,k] \setminus \{i\}, d_A(a, B_i) < \mathrm{d}A(a, B_j)\}, \tag{13}$$

where $d_A(a, B)$ is the geodesic distance from a point a to the set B (ref. 23). Some points of A do not contribute to any influence zone. These points make the skeleton of a influence zone of B in A

$$\mathrm{SKIZ}_A(B) = A \backslash IZ_A(B) \tag{14}$$

$\mathrm{SKIZ}_A(B)$ are the points that do not belong to any influence zone

$$IZ_A(B) = \bigcup_{i \in [1,k]} iz_A(B_i). \tag{15}$$

After the watershed ridge lines are computed, the intensity of the image is modified using morphological reconstruction so that it has the regional minima in the desired locations. The watershed image is computed over the intensity-varied images.

Quantitative analysis

After the watershed transformation, quantitative analysis is performed over the segmented image. Numerical analysis is carried out by calculating the area of the object by one of the available methods. The error percentage is calculated by finding the ratio of the segmented area to the actual area

$$\%\mathrm{Error} = \frac{\mathrm{Area}_{\mathrm{actual}}}{\mathrm{Area}_{\mathrm{seg}}} * 100, \tag{16}$$

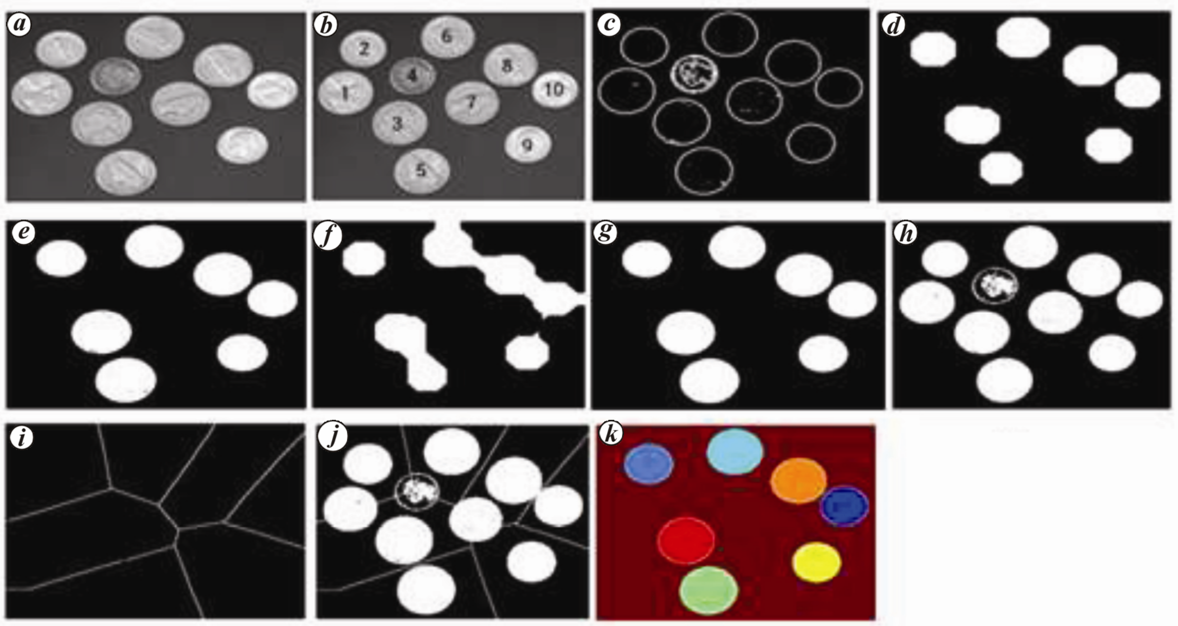

Figure 2. ***a***, Original image[27]; ***b***, Labelled image; ***c***, Gradient magnitude of the image; ***d***, Opening; ***e***, Opening by reconstruction; ***f***, Opening–closing; ***g***, Opening–closing by reconstruction; ***h***, Modified regional maxima superimposed on the original image; ***i***, Watershed ridge lines; ***j***, Markers and objects superimposed on the original image; ***k***, RGB superimposed on the original image.

Table 1. Comparison of results based on the area computation done for LoG, Sobel, Canny, morphological, active contour, Otsu's and marker-based watershed segmentation

Object number	Actual area	Area computed by LoG method	Area computed by Sobel method	Area computed by Canny method	Area computed on morphological-based segmentation	Area computed based on active contour	Area computed based on Otsu's thresholding	Area computed on marker-based watershed segmentation
2	1852	1863	1933	1920	1578	1903	1792	1854
3	2670	2715	2773	2828	2435	2753	2590	2678
5	2751	2774	2834	2874	2540	2896	2695	2751
6	2509	2541	2601	2626	2321	2721	2451	2509
8	2542	2570	2632	2625	2231	2689	2401	2538
9	1851	1864	1955	1920	1696	1963	1782	1891
10	1853	1839	1924	1909	1628	1958	1793	1863

All values in pixels.

$$\%\text{ErrorDiff} = \frac{e(n_{\text{morph}}) - e(n_{\text{mar}})}{e(n_{\text{morph}})} * 100. \qquad (17)$$

The marker-based segmentation result is compared with those of morphological segmentation[19] and other methods.

Results and discussion

The image 'coin.png' is used for analysis. Figure 2 shows the image segmented out using the marker-based watershed transform. Several improvements are made with respect to the edge detection strategies; few of the edge detection methods are combined with morphological operators[24].

The results obtained for morphological operations along with marker-based watershed transform are compared with those of other methods like LoG, Sobel, Canny, morphological-based segmentation, active contour[25] and Otsu's thresholding[26]. From Table 1 it can be inferred that the marker-based watershed segmentation performs better in preserving the area of the coin. It can also be inferred that this algorithm outperforms morphological-based method. The error percentage has reduced effectively, i.e. the area of each coin that is being segmented by marker-based watershed is close to the ground truth area of the original image, indicating that over-segmentation has been reduced effectively. This method also yields exact segmentation of a few objects, which is indicated by zero error. On the other hand, the morphological

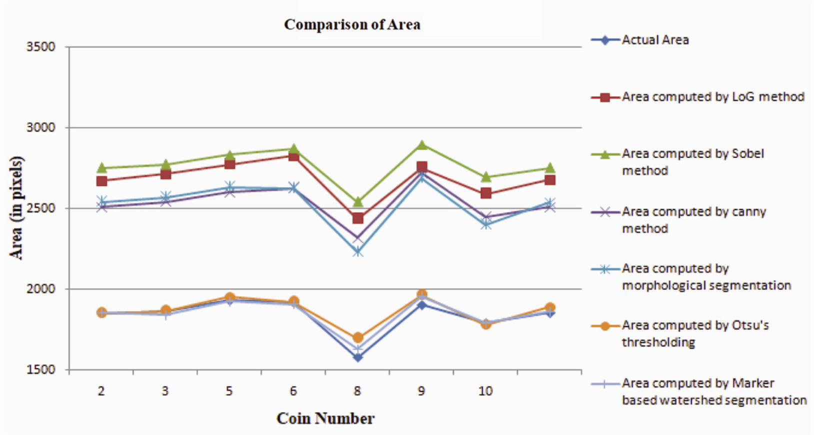

Figure 3. Area comparison in pixels for various objects present in the image (object versus error %).

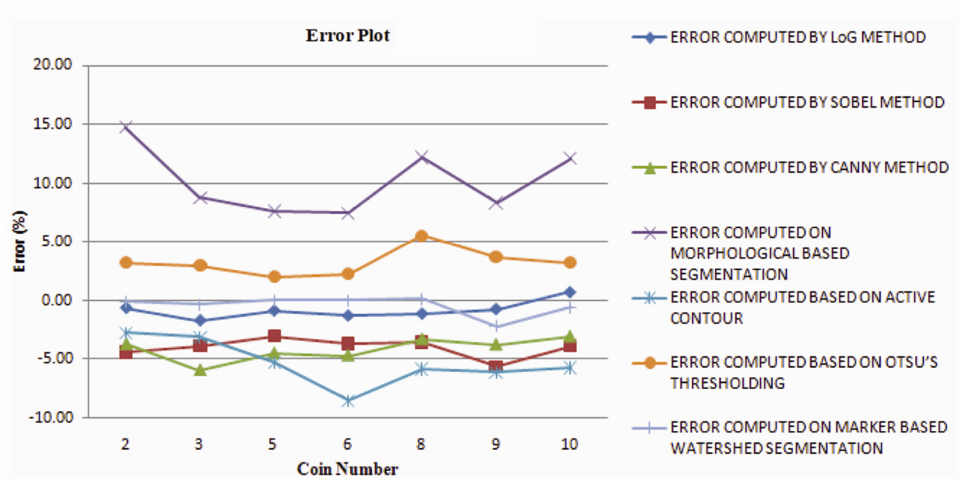

Figure 4. Error comparison among LoG, Sobel, Canny, morphological and marker-based watershed segmentation methods for various objects present in the image (object versus error %).

Table 2. Error comparison results among LoG, Sobel, Canny, morphological, active contour, Otsu's and marker-based watershed segmentation methods

Object number	Error of LoG method	Error of Sobel method	Error of Canny method	Error of morphological-based segmentation	Error of active contour	Error of Otsu's thresholding	Error marker-based watershed segmentation
2	–0.59	–4.37	–3.67	14.79	–2.75	3.24	–0.11
3	–1.69	–3.86	–5.92	8.80	–3.11	3.00	–0.30
5	–0.84	–3.02	–4.47	7.67	–5.27	2.04	0.00
6	–1.28	–3.67	–4.66	7.49	–8.45	2.31	0.00
8	–1.10	–3.54	–3.27	12.23	–5.78	5.55	0.16
9	–0.70	–5.62	–3.73	8.37	–6.05	3.73	–2.16
10	0.76	–3.83	–3.02	12.14	–5.67	3.24	–0.54

segmentation, Active contour and other methods have a comparatively higher error for every object compared to the proposed method.

From Figure 3, it is evident that marker-based watershed has less error percentage compared to other methods. It is also be seen from the figure that the morphological-based segmentation results in significant under-segmentation, whereas the active contour method yields over-segmentation.

Table 2 shows the error comparison between the methods. LoG, Sobel, Canny, active contour and Otsu yielded negative error percentage. This indicates the over-segmentation factor; it traces out the pixels which are not a part of the respective coins. On the other hand, the error obtained for morphological-based segmentation and watershed-based segmentation is positive. Comparing the two, it can be inferred that the accuracy of the marker-based watershed segmentation is high compared to the morphological segmentation.

Figure 4 shows that the marker-based watershed transform line is around the zero error axis, whereas the morphological segmentation has higher positive error and the other methods have negative errors. The number of area pixels of the marker-based watershed and the original area pixels is almost same, indicating that the watershed algorithm performs better compared to the other edge-detection methods.

Conclusion

A methodology which incorporates the concept of marking along with the traditional watershed segmentation has been implemented. It addresses the drawbacks of the conventional watershed algorithm, which include over-segmentation and noise sensitivity. The proposed algorithm is compared with other image segmentation techniques like the Sobel, Canny, LoG, morphological-based algorithm, contour-based and Otsu's algorithm. It is found that the proposed algorithm is efficient, reliable, robust, and provides result without much noise as well as works on complex images. The proposed method also reduces the error percentage by 95, effectively leading to a higher scale of accuracy.

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