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Novel Machine Vision Tools Applied in Biomechatronic Tasks

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Abstract

The article describes a novel machine vision tools for moving objects detection. The methods are based on spatial or frequency analysis and consecutive segmentation process. The moving objects are captured by video camera and image analysis is used for evaluation. This fact is very important in medical or biomechanical applications, when the moving objects are needed to determine patient's diagnosis or patient's behavior. Machine vision tools are applied for determination of movement frequency or trajectory.

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Nomenclature

x_c, y_c	coordination of reference point
x_i, y_i	coordination of point
r_i, θ_i	distance and orientation from reference point to point on curve
f(i,j)	result image after Moravec operator
g(i,j)	original image pixel value
g(k,e)	original image pixel surroundings

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1. Introduction

Modern medical diagnostic and measurement methods are situated in the intersection of conventional science and industry branches: physics, electronics, informatics, telecommunications and medicine. The modern medical imaging techniques represent a relatively highly specialized technological approaches. These techniques require cooperation between several industrial branches. The correct image creating of microscopic objects is a combination of appropriate lighting and correct adjustment of the microscope. The high-speed process such as oscillation of microscopic biomechanical objects represented by cilia of respiratory epithelium can be captured by high-speed camera with adequate resolution and suitable scanning frequency. Another challenge is the storage and handling of huge amount of data. This process is done for image processing to obtain important information such as frequency from scanned images.

The methods used for image processing including adjusting brightness and contrast, filtering unwanted artifacts, detecting edges of objects, segmentation and morphological filtering for the image analysis purposes. The unwanted artifacts are for example air bubbles or erythrocytes. The artifacts can be detected or removed by application of machine vision tools. This methods facilitates the identification of moving objects and improve accuracy of evaluated parameters. Evaluated parameters leads to better and faster diagnosis of the respiratory tract diseases.

2. Methods

2.1. Geometric Matching

Searching and matching algorithms, such as the pattern matching algorithm or geometric matching algorithm, find regions in the inspected image that contain information similar to the information in the template. This information, after being synthesized, becomes the set of features that describes the image. Pattern matching and geometric matching algorithms use these sets of features to find matches in the inspected images. [1] – [3]

The geometric matching process consists of two stages: learning and matching. During the learning stage, the geometric matching algorithm extracts geometric information from the template image. The algorithm organizes and stores the information and the spatial relationships between these features in a manner which facilitates the faster searching in the inspected image.

During the matching stage, the geometric matching algorithm extracts geometric information from the inspected image which corresponds to the information in the template image. After that, the algorithm finds matches by locating regions in the inspected image where features align themselves in spatial patterns similar to the spatial patterns of the features in the template.

Matching algorithm includes two geometric matching methods. Both geometric matching techniques rely on curves extracted from image to perform the matching. The two geometric matching techniques differ in how the curve information is used to perform the matching. The edge-based geometric matching method computes the gradient value of the edge at each point along the curves found in the image and uses the gradient value and the position of the point from the center of the template to perform the matching. The feature-based geometric matching method extracts geometric features from the curves and uses these geometric features to perform the matching.

A curve is a set of edge points that are connected to form a continuous contour. Curves typically represent the boundary of certain structures in the image. In geometric matching, curves are the underlying information used to represent a template and to match the template in an inspected image.

The curve extraction process consists of three steps:

- finding curve seed points,
- tracing the curve,
- improving the curves.

2.2. Edge-Based Geometric Matching

The edge-based technique utilizes for matching the generalized Hough transform method. The generalized Hough transform is an extension of the Hough transform to detect arbitrary shapes. [1] – [3]

During the learning stage the two steps are executed- edge point extraction and R-table generation. During the edge point extraction stage, the algorithm detects curves in the image and computes the gradient value at each edge point along the contours. The gradient value specifies the orientation of the tangential line at each point along the contour.

The generalized Hough transform uses a lookup table called an R-table to store the shape of the object. The R-table allows the generalized Hough transform to represent any arbitrary shape and does not require a parametric description of the object.

The algorithm uses the following steps to compute the R-Table of a given shape (specified by the curves that are detected along the boundary of the shape).

- The algorithm selects the center of the template image as a reference point (x_c, y_c).
- For each point (x_i, y_i) along the curves in the template image, the algorithm calculates the distance and orientation (r_i, θ_i) from the reference point as shown in the figure Fig. 1:

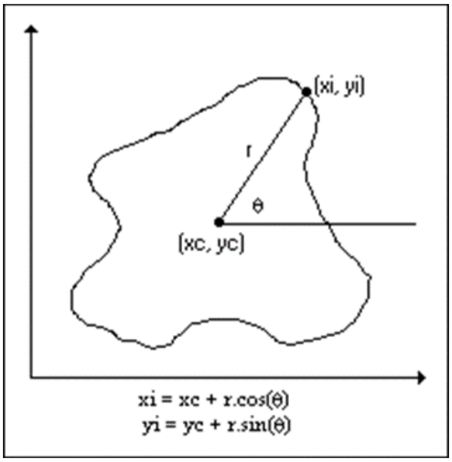


Fig. 1. Distance and orientation calculation of the curve

- The algorithm stores the (r_i, θ_i) value for each point in the R-table as a function of ø

After the algorithm adds all points along the curves in the template image, the R-table represents the information that is learned from the template. The R-table can be used to regenerate the contour edge points and gradient angles at any point in the image during the matching phase.

The R-table stores the shift-invariant representation of the template object. Because each combination of scale and rotation requires a unique R-table, a template that allows variance in scale and rotation can occupy a large amount of memory.

The matching stage consists of three steps:

- edge point extraction, which is similar to the edge point extraction that occurs during the learning stage,
- generalized Hough matching,
- match refinement.

The edge points in the image are detected using the curve extraction process. If the size of the template image was reduced by sampling, then the inspected image is reduced by the same sampling factor before the curves are detected. The gradient value is computed and stored at each edge point along the detected curves.

The generalized Hough matching follows after edge point extraction. The matching process begins after the algorithm finds edge points and their gradient values in the inspected image. The matching process consists of the following steps:

1. The algorithm creates an accumulator, which stores candidate match locations in the inspected image.
2. The algorithm performs the following actions for each edge point (x, y):
   - The algorithm uses the gradient value ø to index into the R-table and retrieve all the (r, θ) values.
   - The algorithm computes the candidate reference point for each (r, θ) value as follows:
     $x_c = x - r\cos(\theta)$
     $y_c = y - r\sin(\theta)$
   - The algorithm increases the count in the accumulator for the location of the candidate reference point.
3. The algorithm finds the local peaks in the accumulator. These peaks represent possible match locations.

In case of matching for variation in rotation or scale, the algorithm builds an accumulator for each possible combination of rotation and scale, and performs steps 1–3 for each accumulator. The algorithm processes the peaks in each accumulator to find the best matches.

Match refinement is the final step in the matching stage. The algorithm uses curves extracted from both the template image and inspection image to ensure increased positional, scalar, and angular accuracy.

2.3. Feature-Based Geometric Matching

Following curve extraction, the learning stage consists of two steps – feature extraction and representation of the spatial relationships between the features. [1] – [3]

Feature extraction is the process of extracting high-level geometric features from the curves obtained from curve extraction. These features can be lines, rectangles, corners, or circles.

First, the algorithm approximates each curve using polygons. Then, the algorithm uses the line segments forming these polygons to create linear and corner features. These linear features are used to compose higher-level rectangular features. The curves or segments of curves that cannot be approximated well with polygons or lines are used to create circular features.

After the algorithm extracts high-level geometric features from the template image, the features are ordered based on some criteria (e.g. type, strength or saliency). After the features have been ordered, the best are chosen to describe the template.

Given two features, the algorithm learns the spatial relationship between the features, which consists of the vector from the first feature to the second feature. These spatial relationships describe how the features are arranged spatially in the template in relationship to one another. The algorithm uses these relationships to create a model of features that describes the template. The algorithm uses this template model during the matching stage to create match candidates and to verify that matches are found properly.

The matching stage consists of five main steps. The first two steps performed on the inspected image are curve extraction and feature extraction, which are similar to the curve extraction and feature extraction that occur during the learning stage. The final three steps are feature correspondence matching, template model matching, and match refinement.[7]

Feature correspondence matching is the process of matching a given template feature to a similar type of feature in the inspected image, called a target feature.

Template model matching is the process of superimposing the template model from the learning step onto a potential match in the inspection image to confirm that the potential match exists or to improve the match. After superimposing the template model onto a potential match, the presence of additional target features found in accordance with the template model and its spatial relationships to existing features confirms the existence of the potential match and yields additional information that the algorithm uses to update and improve the accuracy of the match.

Match refinement is the final step in the matching stage. Match refinement carefully refines known matches for increased positional, scalar, and angular accuracy. Match refinement uses curves extracted from both the template image and the inspected image to ensure that the matches are accurately and precisely found.

2.4. Color Location

Color location is used to quickly locate known color regions in an image. A model or template which represents the color that are being searched is created. Machine vision application then searches for the model in each acquired image, and calculates a score for each match. The score indicates how closely the color information in the model matches the color information in the found regions. [1] – [3]

Color can simplify a monochrome visual inspection problem by improving contrast or separating the object from the background. Color location algorithm provide a quick way how to locate regions in an image with specific colors.

The color location measure the similarity between an idealized representations of a feature, called a model, and a feature that may be present in an image. A feature for color location is defined as a region in an image with specific colors. [8]

Color location is useful in many applications. The color location can be used in the following general applications—inspection, identification, and sorting.

Inspection detects flaws such as missing components, incorrect printing, and incorrect fibers in textiles. A common pharmaceutical inspection application is inspecting a blister pack for the correct pills. Blister pack inspection involves checking that all the pills are of the correct type, which is easily performed by checking that all the pills have the same color information.

Identification assigns a label to an object based on its features. In many applications, the color-coded identification marks are placed on the objects. Color matching locates the color code and identifies the object.

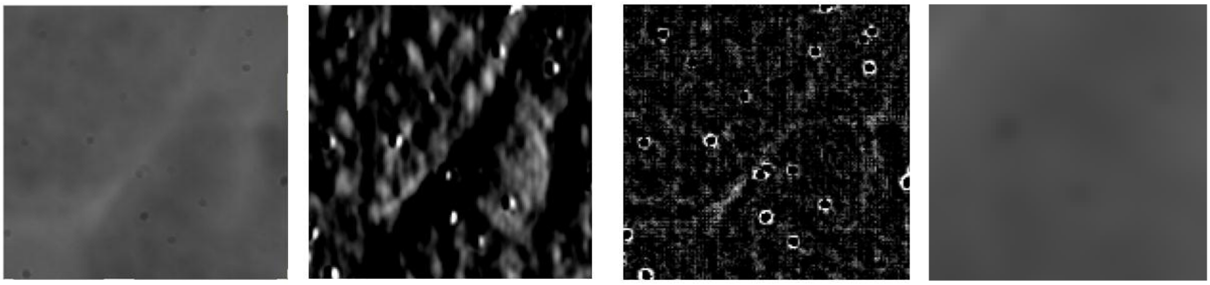
3. Experimental results

A real video with moving cilia contains different artifacts such as red blood cells or air bubbles after preprocessing. Classification of cilia and artifacts is important for correct evaluation of the cilia kinematics. For this reason, it is necessary to choose the correct method of segmentation. Therefore artifacts are normally circular objects or background of an image.

3.1. Algorithm based on Hough transform

An algorithm was developed to remove unwanted particles. The algorithm consists of a filter, equalization and thresholding the image. The resulting image is a binary image with a lot of fine particles. Morphological operators are applied to the binary image to remove the fine particles. Finally, the Hough algorithm is applied to find the circular objects, which represent red blood cells or air bubbles in the image.[4], [5]

Color image is convert to grayscale image in first step of this algorithm. The conversion can be done by single color extraction or colors planes averaging. An image filters are used to improve input grayscale image after conversion. The Gaussian, Laplace or gradient filer can be used. The results of filtering are shown in Fig. 2.



a) b) c) d)

Fig. 2. a) Original image, b) gradient filter 7x7, c) Laplace 7x7, d) Gaussian 7x7

The best results for next processing was done with Gaussian filter 7x7. The equalization process can be done for visual image enhancement. A Moravec operator is applied after filtering.

The Moravec operator determines changes in grayscale image based on intensity of adjacent pixels. The resulting image is calculated by equation (1).

$$f\ (i,j) = \sum_{k=i-1}^{i+1} \sum_{e=j-1}^{j+1} |g\ (k,e) - g(i,j)| \tag{1}$$

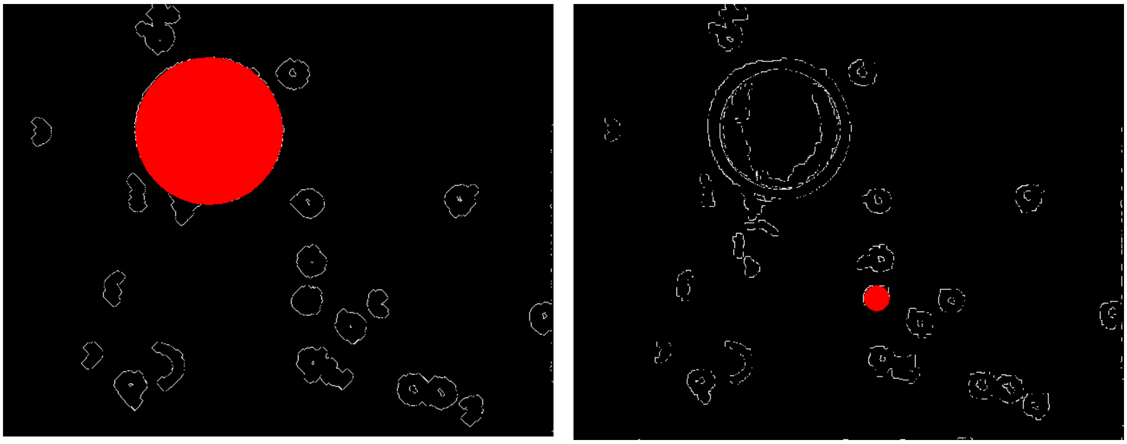
where *i, j* are pixel coordinates and *k, e* are pixel surroundings.

The resulting values are transformed into range 0 – 255. After this process there is applied thresholding for binary image creation. The best results for next processing were achieved with condition that the value of histogram thresholding is 10% of the maximal value. The morphological operators are applied for binary image enhancement to remove small particles or connect the important area. The best results are achieved with opening operator followed with gradient operation for edge thinning (Fig. 3).

a) b) c)

Fig. 3. a) Opening binary image, b) inner gradient morphological operator, c) outer gradient morphological operator

The Hough transform is applied for circular object detection [6]. The diameter of circle must be set for proper searching of circular objects. The results for various diameters of Hough transform are in Fig. 4.



a) b)

Fig. 4. Circular objects detected by Hough transform with diameter a) 170 – 180 pixels, b) 30 – 40 pixels

3.2. Object identification based on color information

In certain images there is obvious that various artifacts of the background (e.g. air bubbles) have apparently different colors. In these cases can be used for segmentation the Color location method. Based on this method the algorithm was created which is able to load a color image and select regions in an image that contain the particular color information we want to use as a reference. After the analysis the application was able to identify the position of an artefact using the comparison of the color information in the whole image to the reference color spectrum. The kernel size, color sensitivity and matching score (in ‰) can be manually adjusted. Selected color region which is used as a reference is displayed in the middle of front panel (Fig. 5).

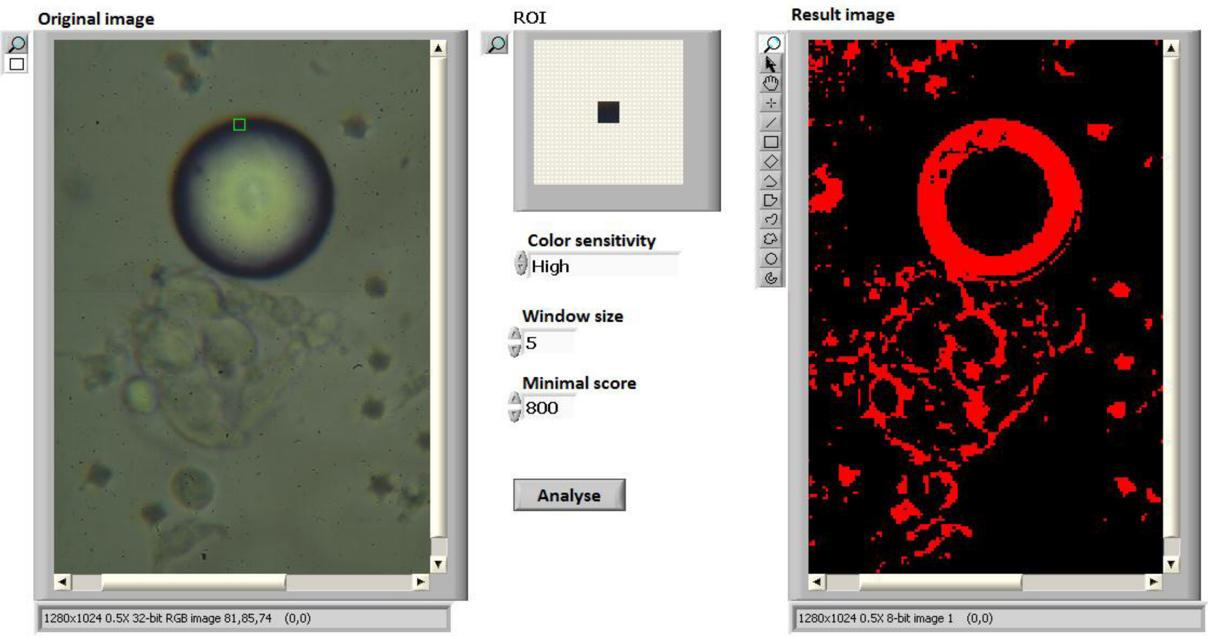


Fig. 5. Front panel of Color location input parameters setting

If all of the parameters are set properly, the resulting binary image contains a small number of noise elements with recognizable circle element which might be further detected using the Hough transform.

3.3. Object identification based on statistic parameters

The Color location method in not suitable for grayscale images because they do not contain any color information, only the information about brightness value of each pixels. These images can be described by chosen statistic parameters, mean value and standard deviation. The proposed theoretical analysis of the algorithm is based on the assumption that our specific medical images contain four types of structures: the cilia of respiratory epithelium, epithelium cells, erythrocytes and background. Several small regions size 15x15 were selected in part of an image containing each structure. After that the histogram was displayed and the mean and standard deviation were calculated.

The resulting data shows that the standard deviation of the background was much lower than the standard deviation of the other structures. Based on these results there might be programmed an algorithm similar to Color location method which would use the kernel sized 15x15 sliding through an image and count the standard deviation for each 15x15 region. If the standard deviation is lower than 1.5, all pixels in certain region will be replaced by logic 0 and vice versa. Using these statistic parameters it might be possible to distinguish the background from the other structures.

Conclusion

The principle of Hough transform algorithm is in theory quite simple. It is used in the detection of circular objects in the image which means that it is necessary to step through two-dimensional array (pixel by pixel) and for each value of logical 1 in an image render a circle of certain radius. For an arbitrary radius of the circle this means a huge amount of computational operations which are considerably time consuming and quite difficult. For practical reasons, it is appropriate to narrow down the wanted radius of circles only to a few values.

Another proposed algorithm uses for image segmentation a method called Color location. This method has proven to be suitable for images which contain artifact in form of an air bubble. The resulting image of our application was a binary image with a well-defined circular object which might be further detected using the Hough transform.

The last part of this article discusses the possibility of detection of the background based on statistical parameters. Appropriate parameter on the basis of our analysis proved to be the standard deviation for kernel size 15x15 pixels. In all cases the value of standard deviation of image background was lower than 1.5. This difference in the standard deviation for the background area from the areas of blood cells and ciliary epithelium, could be used for designing of other applications for image analysis.

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