TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol. 12, No. 8, August 2014, pp. 6173 ~ 6180
DOI: 10.11591/telkomnika.v12i8.5387

Image Segmentation of Adhering Bars Based on Improved Concavity Points Searching Method

Guohua Liu*, Bingle Liu, Qiujie Yuan, Zhenhui Huang
School of Mechanical Engineering, Tianjin Polytechnic University, Tianjin 300387, China
*Corresponding author, e-mail: guohualiumail@163.com

Abstract

It is difficult to track, count and separate the bars moving at a high speed on production line for their overlap under occlusion. Therefore, it is necessary to establish a reliable, practical splitting mechanism for the adhered bars. This paper proposed a new solution to the problem of bars adhesion: the plane array camera was utilized to acquire the images of moving bars so as to recognize the centroid coordinates of the bars ends and compute their area with a Blob algorithm, two geometric parameters were utilized to detect adhered bars, and the presence of adhered bars was analyzed according to the convex hull. For the adhered bars, the segmentation points were searched using scanning method by a series of the rules to determine the optimal segmentation line. The proposed method can segment the adhered bars effectively with matched concavity points. The experimental results show that the method can well segment and count bars moving at a high speed on production line, with the counting accuracy near to 100% and the recognizing time in millisecond.

Keywords: *adhesion, Blob algorithm, concavity analysis, concave points, segmentation, bars*

Copyright © 2014 Institute of Advanced Engineering and Science. All rights reserved.

1. Introduction

With the popularization of negative deviation rolling technology, to ensure the economic interests of rolling mills, it is necessary to count and separate the steel bars precisely that the bars of high-speed production lines need to be reliably detected, located and determined the mutual positional relationship. Therefore, Enterprises pay more and more attention to the method that can quickly and accurately achieve automatic counting of steel bars.

However, in actual production, due to production process and complicated production environment of steel bars, there is usually existing severe noise in the acquired image for a couple of reasons: the light changing frequently, the motion image blurring caused by the quick movement of steel bars, the dark or blue sections for oxidation. Especially, the image distortion caused by the monocular image acquisition will generate occlusion and adhesion phenomenon on the edge of images. In addition, misaligned bars will cause the same problem. All the problems will make it difficult to track, count and separate the steel bars on production line [1].

After image threshold processing and binary processing, the adhesive targets are in the same connected domain because the targets have the same color and texture features. So, these targets will be treated as one target and errors are easy to occur in the subsequent processing. Moreover, there is almost no gray difference or gray gradient difference among the adhesive oval targets, which makes it difficult to identify different regions. Therefore, it is necessary to separate the adhering bars into individual goals via a series of processing, which is the adhesion target segmentation [2].

Image segmentation of adhering steel bars or other oval objects is the precondition for subsequent image analysis and feature extraction. On the problem of adhering targets segmentation, many scholars have proposed different methods, such as mathematical morphology operations, improved watershed transform, and active contour tracking. The traditional watershed segmentation method [3] is prone to cause over-segmentation result, and the accuracy of object extraction is not high.

The research for the image segmentation of adhered steel bars or other oval objects has obtained some achievements at present. The method of image segmentation and recognition based on the oval assumption has been proposed in reference [4], combined with the mathematical morphology, it has solved the problem of the adhered steel bars, and realized

Received December 18, 2013; Revised April 7, 2014; Accepted April 20, 2014

the counting of bars, but with low accuracy. Wu separated steel bars from the background by means of active contour model, and he realized the segmentation and counting of the steel bars by using image segmentation, edge extraction and mathematical morphology [5]. Zhang proposed the method which based on template matching and variable threshold segmentation for detection and positioning of bars, to some extent, which can overcome the bar section adhesion, occlusion, oxidation and other interference [6].

For the problem of the adhered bars in the image, reference [7] took the following actions: preprocessing the collected original bar image; then processing each bar in the image into a single pixel by corrosion and thinning algorithm, which can realize the segmentation of adhered bars preliminarily; in the end, using the algorithm of shrinkage and detecting the endpoint of the line, to realize the one to one correspondence between single pixel and related steel bar on the original image [7]. However, this method can not solve the occlusion problem.

A method for image segmentation based on local binary pattern and region competition was proposed in the reference [8]. In this method, the region competition algorithm was improved, a new region competition hypothesis was introduced according to the characteristics of the bar image segmentation, and an iterative algorithm was proposed, in which the energy can be converged to the local minimum. But the calculation of this method is so complicated that this method is not suitable for real-time counting.

Reference [9] uses the area method to separate and count the adhered steel bars, its theory is to calculate the average area of the bars section at first, then to calculate the number of bars according to the area of each connected domain. Error in this method will be large.

Reference [10] takes advantage of the improved watershed algorithm to handle the adhering bars in the image. Firstly, the image is pretreated before using watershed algorithm; and then, the method of gradient operator and mathematical morphology must be used to avoid over-segmentation. Finally, watershed algorithm based on distance transformation is used to realize the segmentation of adhering bars. However, this method generates considerable error for occlusion bars image.

Reference [11] pretreated the bars sections in the image acquired in real time by use of graying, smoothing, and binarization, and proposed a method of counting oval objects based on region growing method and linear notation method. This method can achieve the purpose of counting and separating the adhering bars.

The above segmentation method for adhered bars image can not meet real-time requirements not only on the accuracy but also on the processing speed. Over-segmentation, excessive operation or poor accuracy does not suit for high-speed and real-time processing on bars production line. In this paper, we will study on this issue in order to resolve the problem of adhering bars segmentation. First, we can obtain an accurate separation location between the bars; and this will lay solid foundation for target tracking, counting and separating bars by servo system.

2. Image Preprocessing of Steel Bars

In this paper, images are collected through the Basler plane array camera, whose resolution is 1296×966, frame rate is 30fps, and collection field is 700mm×200mm. One image can be acquired and processed within 30ms. The acquired image of bars in the highlight blue LED light source is shown in Figure 1.

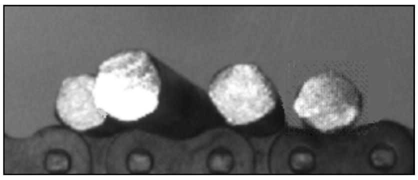

Figure 1. Image of Bars (the tenth frame)

There is usually severe noise in the image collected from the camera for a couple of reasons: First, shapes of bars sections are different; second, field environment is complex; third, light changes frequently. Therefore, image preprocessing is necessary in this paper, and the main means are image threshold segmentation and filtering.

First, processing of image threshold segmentation must be done to the collected images to eliminate the influence of background [12]. Then, assume that the image region is $f(x,y)$, and select the appropriate T as the threshold to obtain binary image through image binarization. The binary image region is $f'(x,y)$. As is shown in Figure 1, sections of bars differ from the background obviously due to light irradiation, thus T will be set as average gray value for the whole image.

Aiming at the noise jamming problems in the image after binarization, median filtering can remove the noise [13]. Binary median filter is applied for in this paper by using 4×4 mask. Figure 2 is the image after pretreatment.

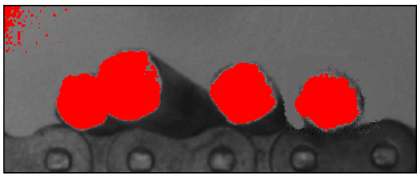

Figure 2. Pretreatment of the Image

3. Blob Analysis

Blob analysis can provide the information of the image about Blob number, location, shape, and orientation, etc; it can also provide the geometric topology of the related Blob.

In this paper, the bars sections can be extracted quickly and accurately by using Blob algorithm, and the length, width, area, and centroid coordinate of each Blob can be calculated. After pretreatment, the target region has become an independent connected domain. This paper extracts the Blob of bars sections of each frame image through eight neighborhood Blob analysis, and calculates the centroid of the target region.

3.1. Blob Recognition

The binary image is $BI(x,y)$ (*BI* for short) after pretreatment, and it can completely be divided into several sub-regions $BI_i(x,y)$, these sub-regions are formed by m Blob and a background [14].

The shape characteristic of the Blob region is described by using the moment [15], for one Blob image $\{I(x,y)\}$, its $(p+q)$ moment is as follows:

$$M_{p,q} = \sum_{(x,y)\in I(x,y)} I(x,y)x^p y^q \tag{1}$$

As is shown in formula (1), (x,y) is interior point or boundary point of Blob domain, for the binary image, the value of $I(x,y)$ is 1(Inside Blob) or 0 (Outside Blob). Moreover, moment sequences $\{M_{p,q}\}$ is only identified by $I(x,y)$.

Particularly, 0 moment of the image is as follows:

$$M_{0,0} = \sum_{(x,y)\in I(x,y)} I(x,y) \tag{2}$$

Formula (2) is the area of Blob region in pixels. Exclude interference region of pseudo bars Blob using feature histogram method according to the Blob region features, and count $M_{0,0}$ of each Blob.

3.2. Blob Mark

In fact, when Blob analysis is carried out on the bar images, there is no need to analysis the whole image; in this paper, we set the interest region in order to significantly reduce calculation. Centroid ($\bar{x}$, $\bar{y}$) of the Blob region can be obtained by formula (3).

$$(\bar{x},\bar{y}) = (\frac{M_{1,0}}{M_{0,0}}, \frac{M_{0,1}}{M_{0,0}}) \quad (3)$$

Mark the centroid and serial number of each Blob region from left to right. Figure 3 is the analysis result of Blob image. Table 2 shows parameter values of each Blob.

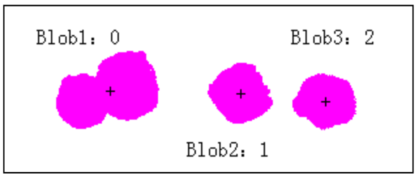

Figure 3. Analysis Result of Bars Blob

Table 1. Blob Parameter Values (pixels)

No.	Area	Centroid abscissa	Centroid ordinate
0	3216	80	64
1	1590	180	65
2	1519	242	73

4. Concave Points Extraction and Segmentation of Adhering Bars

Each independent Blob region of bars image is identified after image threshold segmentation, denoising and Blob analysis. However, some of the targets are one connected regions composed of several bars such as the Blob1 in Figure 3. So it is necessary to segment it into independent and non-stick bars in order to ensure accuracy of counting results.

There are two basic characteristics in convexity adhesion target: First, the radial width of connected place is smaller than the target diameter. Second, a pair of concave points is on both sides of target diameter. Based on this characteristic, we use the segmentation algorithm based on boundary concave points searching and boundary tracking [16].

Two problems must be solved to segment the adhering region; the problems are where to segment the adhering region and how to segment the adhering region. Reference [17] proposed an intuitive method for region segmentation. This method mainly includes three steps: first, finding the deepest concave points by concave analysis to be candidate segmentation points; second, selecting the segmentation route; third, selecting the best segmentation line. This region segmentation method based on concave analysis is widely used in cells and grains segmentation, but the process of finding segmentation points is complicated.

In this paper, we must determine whether the bars are adhesions or not at first. If the bars are adhesive we must detect and smooth the edge and find the concave points; then segment the steel bars image through segmentation line determined by a pair of concave points. Now the adhering bars are segmented perfectly.

4.1. Adhesions Test

For each Blob region getting from Blob analysis, we can find the different size between external convex hull and external rectangle when observing adhesions and non-adhesions Blob region. This provides a basis for determining the existence of adhering bars. Therefore, this paper introduces the aspect ratio and area ratio as morphological parameters to establish discriminant model of adhering bars.

The region of interest is detected and expressed with Blob $B(x,y)$, and its external convex hull and external rectangle $R(x,y)$ is drawn as shown in Figure 4 and Figure 5. The width and height of $R(x,y)$ are $R(x,y)(width)$ and $R(x,y)(height)$.

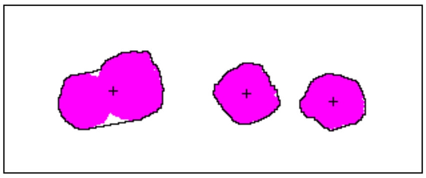

Figure 4. Blob Convex Hull

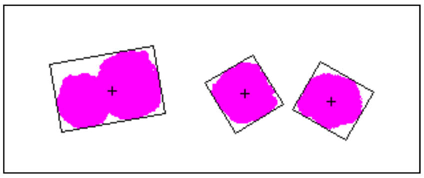

Figure 5. Blob External Rectangle

When the Blob target is too long or too wide, bars are considered to be adhesive. Aspect ratio can be calculated by minimum external rectangle, the formula is as follows.

$$K_{WH} = \frac{R(x,y)(width)}{R(x,y)(height)} \tag{4}$$

The ratio of Blob region area $Area_{Bar}$ to convex hull area $Area_{Convex}$ is the largest when the bars are non-adhesive. So, when the area ratio exceeds a threshold, we can come to the conclusion that the bars are adhesive, and the area ratio formula is as follows:

$$K_A = \frac{Area_{Bar}}{Area_{Convex}} \tag{5}$$

For non-adhesions bars, the K_A is large; but for adhesions bars, the K_A is obviously small. Therefore, an empirical threshold can be used to determine whether there are adhesions bars or not. Moreover, the adhering bars usually appear in the horizontal direction, so bars adhesions appears when K_{WH} is very large. In this paper, we use the threshold K_{WHT1} and K_{WHT2} to determine the existence of bars adhesions. In conclusion, discriminant model can be described as follows:

$$\text{Category} = \begin{cases} K_A < K_T \quad and \quad K_{WHT1} \le K_{WH} \le K_{WHT2} & adhesions \\ \quad others & non-adhesions \end{cases}$$

4.2. Concave Points Extraction

Within the view field, the arrangement of bars along the direction of chain movement may be non-adhesions, two bars adhesions and multiple adhesions. Non-adhesions bars can be easily identified after preprocessing; two bars adhesions and multiple adhesions can also be segmented by using mathematical morphology method if adhesions are not serious. However, partial occlusion caused by field distortion and misalignment of bars will lead to serious adhesions. It is not easy to segment this kind of adhesions by mathematical morphology method. To determine adhesions, we must find the concave points by smoothing processing and make the segmentation line.

In this paper, we assume that the bars sections have convex edges after pretreatment, the concave points in the contact position of two bars can not be covered by other bars, and there is no cavity in the single bar, and its shape is close to a circle or an oval.

We put forward the method of concave point extraction according to adhesions situation. d_l and d_s are major and minor axes convex hull of Blob region, respectively. To improve the searching speed, searching only happens in the minor axis direction.

Standard 1: For the Blob region of adhering bars with obvious external contour, its K_A and K_{WH} are calculate first, then the concave points can be found if K_A and K_{WH} meet the adhesion testing conditions mentioned in 4.1.

We draw the circle with center at the centroid ($\bar{x}$, $\bar{y}$), and radius equal to r_i, which meet the condition $0.25d_s \le r_i \le 0.75d_s$. The arithmetic continuation itself is then carried out by drawing a series of circles $L(r_2)$, … $L(r_i)$, … $L(r_n)$ about this point, and tolerance is 10 pixels.

Standard 3: As the radius increases, $L(r_i)$ and Blob region contours must intersect at the first point.

This point is one of the possible concave points and should be stored in an array $\{g_1(i,j)\}$, and i 、 j are horizontal and vertical coordinates. Then the next point will be found, and the distance between previous point and this point is D; if $D \le 0.25d_s$, radiation continues and this point is in-phase concave point and should be stored in an array $\{g_1(i,j)\}$. With the continuing radiation, if $D > 0.25d_s$, this point is heterogeneous concave point and should be stored in heterogeneous concave point array $\{g_2(i',j')\}$, and i' 、 j' are horizontal and vertical coordinates. This method is repeated until the $L(r_n)$ is radiated. Segmentation line may exist between in-phase concave points and heterogeneous concave points.

Standard 4: Calculate the distance between each point in $\{g_1(i,j)\}$ and $\{g_2(i',j')\}$, and the lines can not exist between the in-phase concave points or the heterogeneous concave points in the array, calculate and find the point satisfying $D_{\min}$ in formula (6), and then the two points are the desirable concave points.

$$\begin{cases} D_{\min} = \min\{D(0), D(1) \cdots D(i)\} \\ D(i) = D((g_1(i,j), g_2(i',j')) \\ \{\{g_1(i,j)\}, \{g_2(i',j')\}\} \in s(contour) \end{cases} \tag{6}$$

$s(contour)$ is Blob region contour in formula (6). Figure 6 shows the extracting process of concave points.

4.3. Determine the Segmentation Line

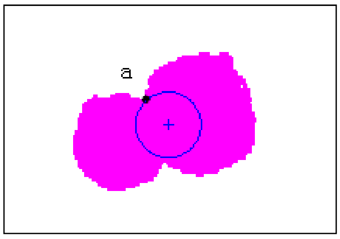

Figure 6(a). Concave points extraction

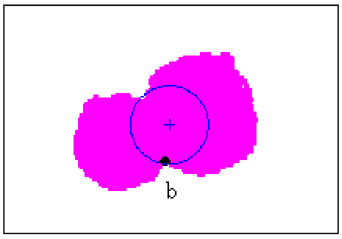

Figure 6(b). Concave points extraction

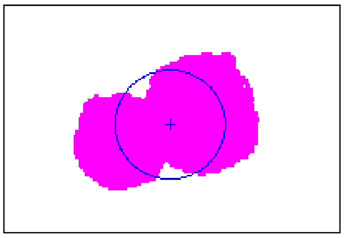

Figure 6(c). Concave points extraction

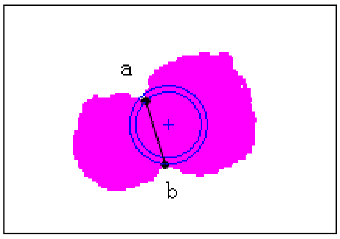

Figure 6(d). Determining the segmentation line

Lines will not exist between in-phase concave point and heterogeneous concave point when we determine the segmentation lines. Then make a straight line between the two concave points which we get to meet the following standards, and this straight line is the segmentation line.

Standard 1: The middle pixel of the straight line connecting the two concave points must be inside the target, in other words, all its pixels belong to Blob region. (Pixels outside the region edge are not in consideration).

Standard 2: Subdomains satisfy the non-adhesions standard mentioned in 4.1 after segmentation.

Thus, the adhering bars are segmented completely, and we can determine the segmentation position and geometric information. The process of determining the segmentation line $\overline{ab}$ is showed in Figure 6(d).

4.4. Set up Parameters

In the standards of adhesions test and concave points extraction, some parameters need to be set up, that is K_T, K_{WHT1} and K_{WHT2}. Generally, these parameters are obtained by a lot of training. The parameters are finally determined through a lot of experiments, $K_T = 0.93$, $K_{WHT1} = 1.45$, $K_{WHT2} = 1.87$.

5. Segmentation Results and Analysis of Adhering Bars

For the video sequences obtained from bars production line, the first step is to extract an image of adhering bars, the second step is to extract Blob concave points, the third step is to segmentation the adhering bars. Computer can complete all process within 30ms for a frame image, so it can satisfy the speed requirements of 25~30f/s. MATLAB program is used in this paper.

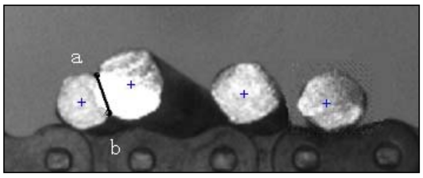

Figure 7. Segmentation Result of Adhering Bars (the 10th frame)

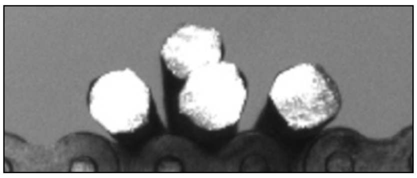

Figure 8(a). Image of adhering bars (the 25th frame)

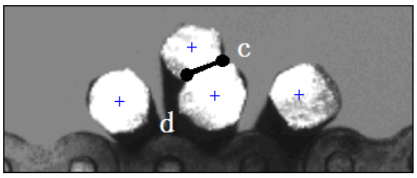

Figure 8(b). Segmentation result of adhering bars (the 25th frame)

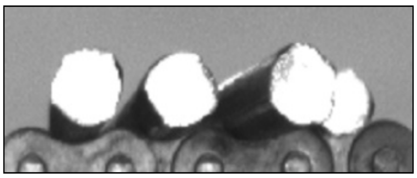

Figure 9(a). Image of adhering bars (the 65th frame)

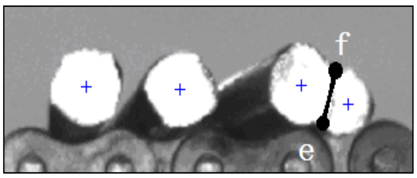

Figure 9(b). Segmentation result of adhering bars (the 65th frame)

The bars segmentation result can be seen clearly in Figure 7, the adhering bars are segmented completely. Figure 8 and Figure 9 show the two other adhering bars images and their segmentation results. Table 2 shows the recognition time. The segmentation results show that the algorithm we used can achieve desired segmentation.

Table 2. Recognition Time

Frame number	10	25	65
Processing time /ms	22	20	18

6. Conclusion

In view of the bar block adhesion problems on the production line, this paper proposes a method based on improved Blob concave points analysis to detect and match the concave points. We propose corresponding segmentation standard to achieve the automatic segmentation of adhered bars. The experimental results show that the algorithm can find the concave points and determine the segmentation lines accurately without over-segmentation. The accuracy, real-time and robustness of the algorithm lay a solid foundation for automatic tracking, counting and separating steel bars on high-speed production line.

References

[1] Davod Aghlmandi, Karim Faez. Automatic Segmentation of Glottal Space from Video Images Based on Mathematical Morphology and the hough Transform. *International Journal of Electrical and Computer Engineering (IJECE)*. 2012; 2(2): 223-230.

[2] Jun Sun, Yan Wang, Xiaohong Wu, Xiaodong Zhang. A New Image Segmentation Algorithm and It's Application in lettuce object segmentation. *TELKOMNIKA Indonesian Journal of Electrical Engineering.* 2012; 10(3): 557-563.

[3] GH Wang, XH Zhou, LL Wei. Image Segmentation Based on Watershed Algorithm. *Computer Simulation*. 2009; 26(5): 255-258.

[4] H Chen, JZ Wang, GM Yao. Pattern Recognition Based on Circular Segmentation for Counting of Bounded Bar Steel. *Journal of Engineering Graphics*. 2004; 25(4): 98-103.

[5] RQ Wu, WM Wang, JH Yang, HG Fu. Automatic detection of contour tongue image based on active contour model. *Journal of Computer Applications*. 2008; 28(S1): 217-219.

[6] D Zhang, Z Xie, JS Ai. Research on rebar section positioning method in online rebar counting system. *Chinese Journal of Scientific Instrument*. 2010; 31(5): 1173-1178.

[7] XY Liu, B Wu, ZQ Su, J Guo, KL Fang. Method for Automatic Counting of Steel Bars Based on Mathematical Morphology. *Control Engineering of China*. 2013; 20(2): 286-288.

[8] YS Zhang, YL Fu, ZG Jiang, WZ Li. Automatic Counting System of Steel Bars. *Journal of Iron and Steel Research*. 2006; 18(9): 1-4.

[9] SD Luo, X Yang, S Sha, WJ Jia. Steel Bar Splitting System Based on Visual Feedback Control. *Mini-micro Systems*. 2005; 26(1): 2000-2004.

[10] ZQ Ma, SS Yin, CY Li, YC Zheng. Improved Vehicle Occlusion Segmentation Method Based on Feature Points Combination. *Journal of Computational Information Systems*. 2013; 9(1): 373-380.

[11] H Wang, G Fan. Recognition and Tracking Method Based on Image of Real-Time and High-Speed Bar. *Journal of Northeastern University(Natural Science).* 2011; 32(2): 281-284.

[12] MX Nixon, AS Aguado. Feature Extraction & Image Processing for Computer Vision, Academic Press, UK. 2012.

[13] Chanho Jung, Changick Kim, Seoung Wan Chae, Sukjoong Oh. Unsupervised segmentation of overlapped nuclei using bayesian classification. *IEEE Transactions on Biomedical Engineering*. 2010; 57(12): 2825-2832.

[14] OS Ahmad, J Debayle, N Gherras, B Presles, G Févotte, J Pinoli. *Recognizing overlapped particles during a crystallization process from in situ video images for measuring their size distributions*. Proceedings of the SPIE, France. 2011.

[15] L Ji. Intelligent splitting in the chromosome domain. *Pattern Recognition*. 1989; 22(5): 519-532.

[16] B Han, ST Wang. *An automatic counting system for oviposited eggs based on digital image processing*. ICEMI 2005: Conference Proceedings of The Seventh International Conference on Electronic Measurement & Instruments. 2005; 6: 539-543.

[17] S Kumar, SH Ong, S Ranganath, TC Ong, FT Chew. A rule-based approach for robust clump splitting. *Pattern Recognition*. 2006; 39(6): 1088-1098.