

1 Development of Ann Based Efficient Fruit Recognition Technique

2 Bhanu Pratap¹, Navneet Agarwal² and Sunil Joshi³

3 ¹ College of technology and Engineering and udaipur

4 *Received: 6 December 2013 Accepted: 2 January 2014 Published: 15 January 2014*

5

6 **Abstract**

7 Use of Image processing technique is increasing day by day in all fields and including the
8 agriculture to classify fruits. Shape, color and texture are the image features which help in
9 classification of fruits. This paper proposes an algorithm for fruits classification based on the
10 shape, color and texture. For shape based classification of fruit area, perimeter, major axis
11 length and minor axis length is calculated. Shape features are calculated by segmenting the
12 object with the background using edge detection techniques. Mean and standard deviation is
13 calculated for the color space like HSI, HSV which can be used for color base classification.
14 Texture features is also calculated to enhance the classification process. Gray Level
15 Co-occurrence Matrix (GLCM) is used to calculate texture features. Artificial neural network
16 is used for classification of fruits. Artificial neural network classifies the fruits by comparing
17 shape, color and texture feature provided at the time of training. MATLAB/ SIMULINK
18 software is used to obtain result. Results obtained are better over the previous techniques and
19 gives the accuracy upto 96

20

21 **Index terms**— fruit classification, gray level co-occurrence matrix, color, texture, artificial neural network.

22 **1 DevelopmentofAnnBasedEfficientFruitRecognitionTechnique**

23 **2 Strictly as per the compliance and regulations of:**

24 Abstract-Use of Image processing technique is increasing day by day in all fields and including the agriculture to
25 classify fruits. Shape, color and texture are the image features which help in classification of fruits.

26 This paper proposes an algorithm for fruits classification based on the shape, color and texture. For shape
27 based classification of fruit area, perimeter, major axis length and minor axis length is calculated. Shape features
28 are calculated by segmenting the object with the background using edge detection techniques. Mean and standard
29 deviation is calculated for the color space like HSI, HSV which can be used for color base classification. Texture
30 features is also calculated to enhance the classification process. Gray Level Co-occurrence Matrix (GLCM) is used
31 to calculate texture features. Artificial neural network is used for classification of fruits. Artificial neural network
32 classifies the fruits by comparing shape, color and texture feature provided at the time of training. MATLAB/
33 SIMULINK software is used to obtain result. Results obtained are better over the previous techniques and gives
34 the accuracy upto 96%.

35 **3 Introduction**

36 n Earlier time's fruits were sorted manually and it was very time consuming and laborious task. Human sorted
37 the fruits on the basis of shape, size and color. Time taken by human to sort the fruits is very large therefore
38 to reduce the time and to increase the accuracy, an automatic classification of fruits comes into existence. The
39 automatic technique incorporate processing of images captured from the test fruits.

40 The features that can be extracted from an image of any fruit are its size, shape, color and texture. These
41 features help the user to classify the fruits in different categories. There are several techniques which can be used

5 C) FRUIT CLASSIFICATION BASED ON TEXTURE

42 to extract the morphological features from an image. For size/ shape, five edge detection techniques are used
43 (Kyaw, Ahmed, & Sharrif, 2009).
44 Intensity (HSI) (Feng & Qixin, 2004) and L*a*b (Gejima, Zhang, & Nagata, 2003) techniques using suitable
45 For color detection in fruits we have to calculate RGB parameters and then convert it into Hue Saturation and
46 algorithms. These techniques are also available with MATLAB toolbox for conversion from RGB into HSI, HSV
47 and L*a*b. Texture is an important feature for characterizing images (Osman & Hitam, 2013). It refers to a
48 change of pixel gray level and color. There are two ways for texture analysis. One is statistical texture analysis the
49 other is structure of texture analysis. The former is the most conventional. Statistical texture analysis methods
50 include spatial autocorrelation method, Fourier power spectrum method, cooccurrence matrix method (Partio,
51 Cramariuc, Gabbouj, & Visa, 2002), gray level difference statistics method and trip length statistics method. a)
52 Fruit classification based on shape Shape modeling is the foundation for object recognition under change of pose,
53 deformation, and varying lighting conditions (Rao & Renganathan, 2002). Shape based classification of fruits
54 takes care of various features like area, perimeter, major axis length and minor axis length. The image generally
55 consists of pixels which includes RGB (Red, Green and blue) components. For calculating these shape features
56 RGB image is converted into gray scale image. (Riyadi, Rahni, Mustafa, & Hussain, 2007) When the image is
57 converted into gray scale image then it represents a different intensity value. There is a difference in intensity
58 value of an object to be classified and the background. A threshold value is decided to separate an object from
59 its background. With the help of this threshold value a gray scale image is converted into binary image in which
60 the value greater than the threshold is 1 and the value lower than the threshold is 0. With the help of this binary
61 image different shape features are calculate. The most common shape features calculated from the image are
62 area, perimeter, major axis length and minor axis length.

63 4 b) Fruit classification based on color

64 An image generally consist of RGB components (red, green and blue) which(Buzera, Groza, Prostean, & Prostean,
65 2008) represents three planes M*N*3. Fruits classified on color bases consist of these three color space RGB.

66 RGB color space is converted into another color space such as HIS, HSV etc (Gonzalez et al., 2004) and for
67 all these converted color space mean and standard deviation is calculated. Each fruit image gives different i.
68 HSV-Color Space HSI stand for hue, saturation and intensity. Pure color attribute of image is described by
69 hue and the amount by which pure color image is diluted by white color is described by saturation. The RGB
70 components are separated from the original image, and the Hue (H), Saturation (S) and Intensity (I) components
71 are extracted from RGB components (Feng & Qixin, 2004). Equations (1), (??) and (3) are used to evaluate
72 Hue, Saturation and Intensity of the image samples. The mean and variance for all these 6 components(Kay &
73 de Jager, 1992) are calculated and color features are stored suitably for later usage in training ANN.?? = ? ??
74 ?? ? ?? 360 ? ?? ?? ??(1)?? = ?????? ?1 ? 1 2 ? (?? ? ??) + (?? ? ??) ?(?? ? ??) 2 + (?? ? ??)?? ? ??
75 ??

76 The saturation component is given by() [] B G R B G R S , , min 3 1 ? ? ? ? ? + + ? = (2)

77 Intensity component is given by ()B G R I + + = 3 1(3)

78 5 c) Fruit classification based on texture

79 Texture is calculated by the outer part of an object which measures the roughness, coarseness and smoothness.
80 Texture is classified by the spatial distribution of gray levels in a neighborhood. It also helps in surface
81 determination and shape determination. Gray level co-occurrence matrix is used to calculate different texture
82 features.(Keller, Chen, & Crownover, 1989) There are two method that can be used to calculate the texture
83 feature of image. One is statistical texture analysis; the other is structure of texture analysis. The former is the
84 most conventional. Statistical texture analysis methods include spatial autocorrelation method, Fourier power
85 spectrum method, cooccurrence matrix method, gray level difference statistics method and trip length statistics
86 method. Texture is using various fields such as in rock. This paper proposes a new technique for region-based
87 skin color classification using texture information. (Clausi, 2002). Color mapping co-occurrence matrix (CMCM)
88 is used to extract the texture information from skin image.

89 Gray level co-occurrence matrix (GLCM) is used to extract texture features in an image. The Grey Level
90 Co-occurrence Matrix, GLCM is also called as Grey Tone Spatial Dependency Matrix (Clausi, 2002) Step 3:
91 determine the threshold to differentiate between object and background using Otsu thresholding.

92 Step 4: convert a gray scale image into binary image.

93 Step 5: calculate area, perimeter, major axis length and minor axis length. Stop ii. Color feature calculation
94 Image captured using digital camera is a colored image which consist of RGB (red, green and blue) component.
95 For color feature extraction RGB is converted into some other color space such as HSI, HSV. HSI stands for hue,
96 saturation and intensity. HSI can be calculated from RGB using equation (??), (3) and (4). For above color
97 space mean and variance is calculated and these calculated values are stored in the artificial neural network.
98 Steps for color features extraction are given in Algorithm 2.?? = ? ?? ?? ? ?? 360 ? ?? ?? ?? (2) ?? = ??????
99 ?1 ? 1 2 ? (?? ? ??) + (?? ? ??) ?(?? ? ??) 2 + (?? ? ??)?? ? ?? ?? ??

100 The saturation component is given by() [] B G R B G R S , , min 3 1 ? ? ? ? ? + + ? = (3)

101 Intensity component is given by ()B G R I + + = 3 1 (4)

102 Algorithm 2: color features extraction Input: image Output: 16 color feature

103 **6 Start**

104 Step 1: Read a RGB image.

105 Step 2: Convert a RGB image into HIS, HSV, L*A*B and YbCbCr.

106 Step3: calculate mean and standard deviation for each color space. Stop

107 iii. Texture feature extraction

108 Texture is calculated by the outer part of an object which measures the roughness, coarseness and smoothness
109 of an image. Texture is classified by the spatial distribution of gray levels in a neighborhood. It also helps in
110 surface determination and shape determination. Gray level co-occurrence matrix is used to calculate different
111 texture features (Clausi, 2002). Gray level co-occurrence matrix (GLCM) is used to extract texture features of
112 an image. The Grey Level Cooccurrence Matrix, GLCM is also called as Grey Tone Spatial Dependency Matrix.
113 It represents the image in the form of tabulation which contains different combinations of pixel brightness value
114 (gray levels) that occurs in an image. To calculate different texture feature like entropy, energy, homogeneity
115 and dissimilarity a gray level co-occurrence matrix is created. It represents the relation between the two pixels
116 at a time, called the reference and the neighboring pixel. The Grey Level Cooccurrence Matrix, GLCM can be
117 analyzed in four different directions are Horizontal (00), Vertical Step 2: Derive Gray level co-occurrence matrixes
118 from the gray scale image for 4 different directions 00,450,900 and 1350.

119 Step 3: Gray level co-occurrence matrix is calculated using equation (5).

120 Step4: Gray level co-occurrence matrix help in calculating contrast, dissimilarity, angular second moment,
121 energy and entropy using equation (??) to (10). Stop.

122 **7 III. Recognition and Classification of Fruits**

123 In this section neural network, training and testing is explained.

124 **8 a) Artificial Neural Network**

125 Neural network is used as a classifier which recognizes fruits and classifies them to the class to which they belong
126 (Cochocki & Unbehauen, 1993). Input layer of neural network depends upon number of input. It has a hidden
127 layer, which consist of neuron which process the information and generate the output. It has five output layers
128 because fruits are classified in five different classes. Neural network perform the classification on shape, color,
129 texture and both color and texture. Result is compared on all these methods and checked which will give the
130 best result.

131 **9 Result and Discussion**

132 Table 1 show the result of classification. Column first of the table gives the image of different fruits. Remaining
133 column gives the percentage of fruits that are classified accurately on shape, color, texture and both color and
134 texture. 100 images of each fruit is taken out of which 50 images is used during the training time and remaining
135 50 image is used for testing. Percentage means how much testing image of each fruits is accurately identified.

136 **10 a) Discussion**

137 Table1 show the comparison between the classification on the basis of shape, color and texture. First the fruits are
138 classified on the basis of shape. For shape classification four parameters are calculated which are area, perimeter,
139 major axis length and minor axis length. It gives good result when different shape fruit are to be classified. By
140 looking into the table it finds that only 72 % of apples are accurately classified. This occurs because most of the
141 time shape of an apple resembles to the shape of Orange and pomegranate. This is the main drawback of shape
142 basis classification. To overcome this drawback a new feature is used that is color .In Table 1 third Column
143 shows the classification percentage on color basis. As the classification accuracy is improved to 94% for apple
144 because apple and orange have different color. But colour basis classification also faces problem when two fruits
145 have same color. Many a times apple and pomegranate have same red color so this will affect the classification
146 and Texture features is also included to perform the classification but it also does not improve the classification
147 because most of the fruits have smooth surface. But the classification accuracy is efficiently improved when color
148 and texture feature are amalgamated. Classification accuracy is improved for all fruits and 96 % pomegranates
149 are accurately classified. V.

150 **11 Conclusion**

151 This paper proposes that when color and texture features are amalgamated, it gives better result over the all other
152 previous method such as shape, color and texture. From the result we can find that shape based classification
153 gives 83.2% accuracy, Color basis gives 90%, Texture basis give 89.60% and results are improved to 96 % when
154 the color and texture features are amalgamated. Hence it can be concluded that color and texture together give



Figure 1: I

Directional Analysis P^0 , P^{45} , P^{90} , & P^{135}

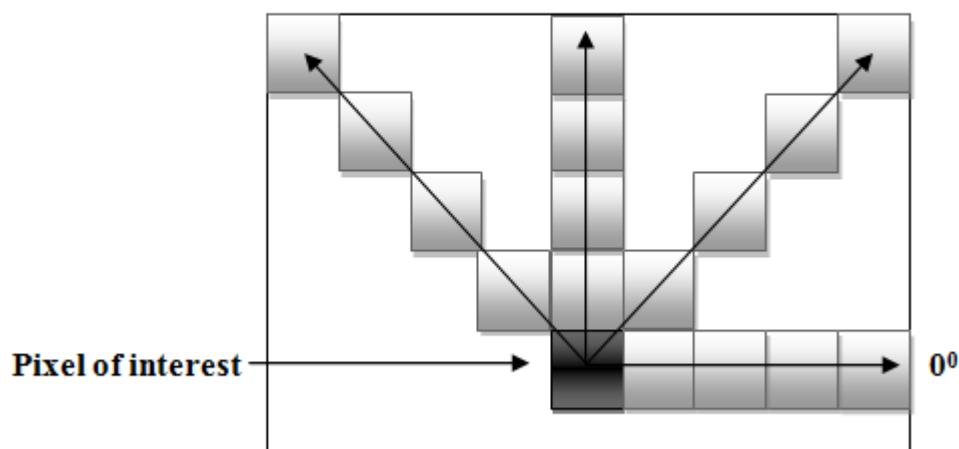


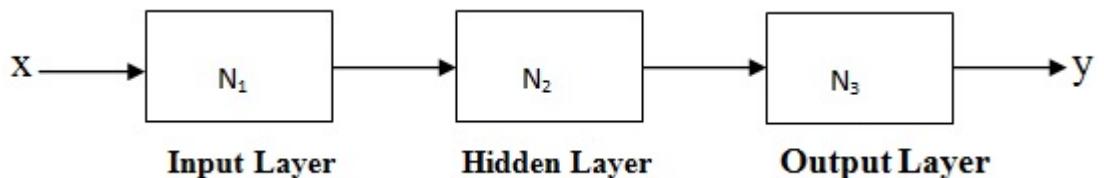
Figure 2:



Figure 3: Figure 1 :



Figure 4: First



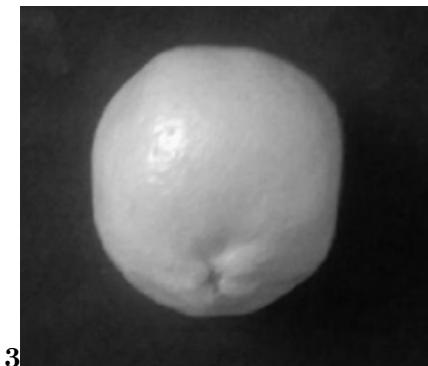
234

Figure 5: Figure 2 :Figure 3 Figure 4 :



51

Figure 6: Figure 5 :Algorithm 1 :



3

Figure 7: Algorithm 3 :

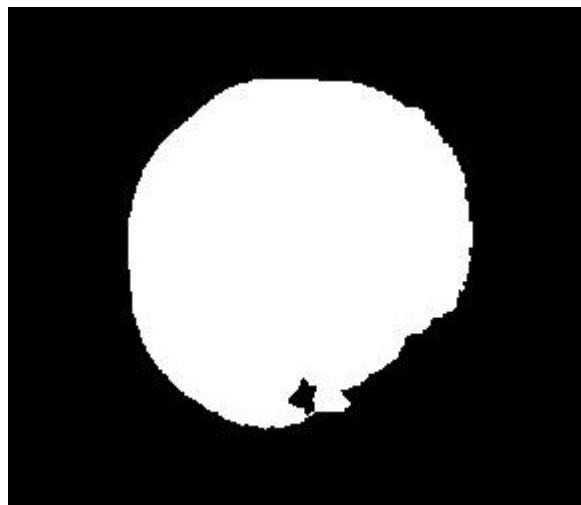


Figure 8:

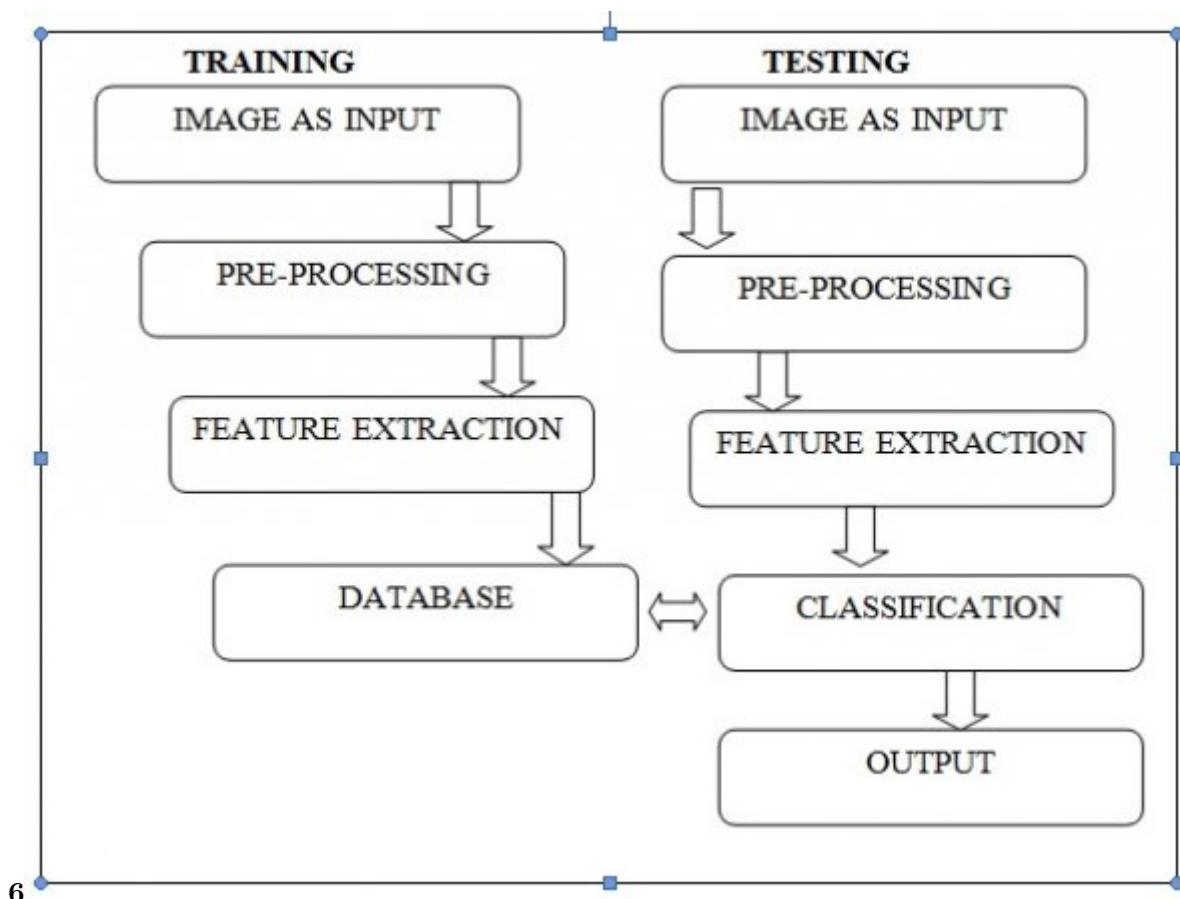


Figure 9: Figure 6 :

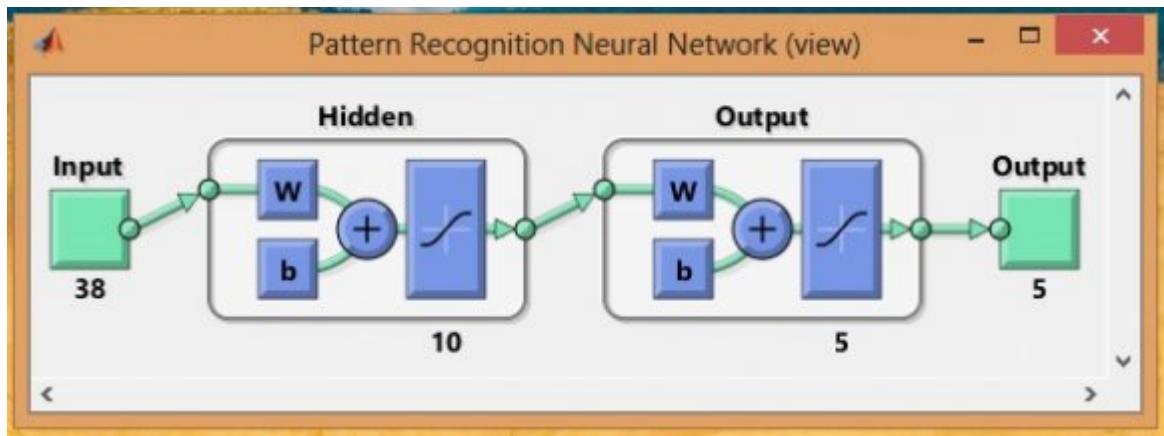


Figure 10:

1

Image of fruits

Accuracy based on (%)
 Shape Color Texture Color
 +
 Textu
 re

Apple	Training=50 Testing=50	72	94	80	96
Banana	Training=50 Testing=50	98	96	96	98
Orange	Training=50 Testing=50	90	90	94	98
Mango	Training=50 Testing=50	86	86	90	92
Pomegranate	Training=50 Testing=50	70	84	88	96

Figure 11: Table 1 :

11 CONCLUSION

155 better result. This result can further be improved by considering the shape also along with color and texture but
156 it may lead to increasing degree of complexity and computation.¹

¹© 2014 Global Journals Inc. (US)Development of Ann Based Efficient Fruit Recognition Technique

157 [Kay and Jager ()] *A versatile colour system capable of fruit sorting and accurate Object classification*, G Kay ,
158 G Jager . 1992.

159 [Clausi ()] 'An analysis of co-occurrence texture statistics as a function of grey level quantization'. D A Clausi .
160 *Canadian Journal of remote sensing* 2002. 28 (1) p. .

161 [Tsoukalas and Uhrig ()] *Fuzzy and neural approaches in engineering*, L H Tsoukalas , R E Uhrig . 1996. John
162 Wiley & Sons, Inc.

163 [Gonzalez et al. ()] R C Gonzalez , R E Woods , S L Eddins . *Digital image processing using MATLAB*, 2004.
164 Pearson Education India.

165 [Gejima et al. ()] *Judgment on level of maturity for tomato quality using L* a* b* color image processing*, Y
166 Gejima , H Zhang , M Nagata . 2003.

167 [Cochocki and Unbehauen ()] *Neural networks for optimization and signal processing*, A Cochocki , R Unbehauen
168 . 1993. John Wiley & Sons, Inc.

169 [Rao and Renganathan ()] 'New approaches for size determination of apple fruits for automatic sorting and
170 grading'. P S Rao , S Renganathan . *Iranian Journal of Electrical and computer engineering* 2002. (2) p. 1.

171 [Jayas et al. ()] 'Review Paper (AE-Automation and Emerging Technologies): Multi-layer Neural Networks for
172 Image Analysis of Agricultural Products'. D S Jayas , J Paliwal , N S Visen . *Journal of Agricultural
173 Engineering Research* 2000. (2) p. 77.

174 [Partio et al. ()] *Rock texture retrieval using gray level cooccurrence matrix*, M Partio , B Cramariuc , M Gabbouj
175 , A Visa . 2002.

176 [Riyadi et al. ()] *Shape characteristics analysis for papaya size classification*, S Riyadi , A A A Rahni , M M
177 Mustafa , A Hussain . 2007.

178 [Kyaw et al. ()] *Shape-based sorting of agricultural produce using support vector machines in a MATLAB/*
179 *SIMULINK environment*, M M Kyaw , S K Ahmed , Z A M Sharrif . 2009.

180 [Osman and Hitam ()] *Skin colour classification using linear discriminant analysis and colour mapping co-*
181 *occurrence matrix*, G Osman , M S Hitam . 2013.

182 [Feng and Qixin ()] *Study on color image processing based intelligent fruit sorting system*, G Feng , C Qixin .
183 2004.

184 [Buzera et al. ()] *Techniques of analysing the colour of produces for automatic classification*, M Buzera , V Groza
185 , G Prostean , O Prostean . 2008.

186 [Keller et al. ()] 'Texture description and segmentation through fractal geometry'. J M Keller , S Chen , R M
187 Crownover . *Computer Vision, Graphics, and Image Processing*, 1989. 45 p. .