INDUSTRIAL VISUAL INSPECTION OF LIME GRANULES BY NEURAL NETWORKS

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ABSTRACT

Lime granule quality inspection is an important task in the pulp and paper industry. In this paper a new method, build-up on a neural network and a path search method, is introduced for lime granule automatic visual inspection. Several correction steps to Landau's method are also introduced. © 1998 Elsevier Science Ltd. All rights reserved.

KEYWORDS

Automatic visual inspection; elliptical objects localisation; neural networks; pulp and paper industry

INTRODUCTION

Recycling is an economical as well as an environmental important issue for most industries. One of the recycling paths in the pulp and paper industry is used to recover bleaching liquor through a causticizing chemical reaction. The efficiency of this reaction is highly conditioned by the quality of the lime applied, namely by its granularity. This fact leads to the need for quality inspection of lime granules. Lime granules are more or less elliptical in shape and, therefore, their automatic visual inspection can be seen as an elliptical object localisation and measurement problem, traditionally solved with a model search procedure such as the Hough transform, least squares or least median squares fitting methods. These strategies exhibit, however, some important drawbacks: (i) low computational efficiency and (ii) low localisation performance whenever in the presence of highly irregular shapes as is the case for most lime granules. In this paper a new and robust method for elliptical object localisation is introduced and applied to the outlined inspection problem. Low level segmentation of lime granule images is not a major difficulty given their bi-modal histograms. We use a minimum cross-entropy principle (Brink and Pendock, 1996) to obtain the binary image. From this image all independent agglomerates of lime granules are identified and their contours grouped. For each cluster the set of contact points between distinct lime granules are then computed, which leads to the definition of a set of elementary arc segments (*EAS*). Finally the obtained *EAS* which belong to the same elliptical object are aggregated together using a multilayer neural network, a path search algorithm and some geometrical-based decision criteria. Main results and conclusions are presented at the end of the paper.

IDENTIFICATION OF EAS

The method is based on the analysis of geometrical relationships between sets of globally convex arc segments, which we shall call *EAS*, obtained from the contours of each multi-connected region (cluster of lime granules). Random dispositions of lime granules may lead to several multi-connected regions formations in the image. Further, it is seen that one or more of these regions may be formed inside a cluster.
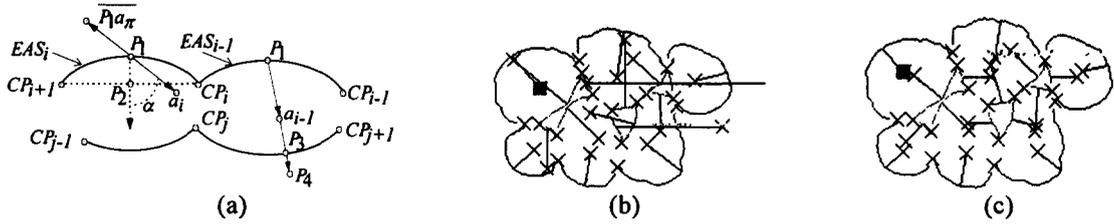
Fig.1: a) Definitions of the points for the geometrical correction steps. b) Centre estimation using Landau's method; c) Centre estimation using Landau's method with correction steps.

However, it is known that all *EAS* that belong to the same elliptical object must be part of the same cluster of lime granules. Therefore, the reconstruction analysis must be carried out for each independent cluster of lime granules. The identification of all agglomerates is performed using a contour grouping strategy based on the Green's discrete theorem (Carvalho *et al.*, 1997). This grouping method assures a fundamental property for the aggregation method: all internal contours are stored with clockwise tracing direction while all external ones are stored with the inverse direction.

The reconstruction of lime granules is based on elementary arc aggregation. It is assumed that an *EAS* is globally convex, therefore non-convex regions of the contour correspond to contact points between distinct lime granules. There are basically two types of strategies to compute these points: (i) polygonal approximation methods and (ii) curvature based methods. In this work we apply the incremental splitting algorithm introduced by (Esplid and Jonassen, 1991) which is computationally very efficient. This algorithm identifies extreme points in non-convex, as well as in convex contour regions. By applying the convexity criterion introduced in (Kim and Rosenfeld, 1991) it is seen that point P_i, obtained with the incremental splitting method, lies in a non-convex region if and only if $|\overline{P_iP_m}|<\Delta$ and P_m lies outside the object (P_m - middle point of the line segment defined by the contour points z position to the right and to the left to P_i; Δ - user defined parameter). An *EAS* is defined by a pair of adjacent contact points $\{CP_i, CP_{i+1}\}$:

$$EAS_i = \{CP_i, ...,P, ..., CP_{i+1}\} \in Contour \qquad (1)$$

Centres and radius of circular arc segments are quite straightforward to estimate using Landau's method (Landau, 1987). However, it is verified that this algorithm fails whenever (i) the arcs are small in size and (ii) the arcs are irregular, as is the case of most *EAS* of lime granules. To overcome these problems a set of geometrical correction steps to the estimated radius and centres obtained with the Landau's method are introduced (R - region of support; P_1 - middle point of the *EAS*; P_2 - middle point of $\overline{CP_kCP_{k+1}}$):

1. The angle formed by the vectors $\overrightarrow{P_1a}$ and $\overrightarrow{P_1P_2}$ is theoretically $0°$. Given the irregular shapes of *EAS*, angles smaller than α (we take $\alpha = 30°$) are allowed, else the estimated centre a is rotated $-\alpha$ degrees with respect to point P_1 (see Fig. 1a).

2. The identified centre a of an *EAS* must lie inside the region R it belongs to, therefore: (i) obtain line segments $\overline{P_1a}$ and $\overline{P_1a_\pi}$ (see Fig. 1 a); (ii) if $|\overline{P_1a} \cap R| > |\overline{P_1a_\pi} \cap R|$ then rotate a as in 1. with $\alpha = \pi$; (iii) if centre a lies outside R then compute point P_3 (see Fig. 1 a) and take $a = 0.5\,(P_1+P_3)$.

3. For smooth arc segments it is seen that the *modulus* of the diameter is twice the *modulus* of the radius with the same direction. This property enables the correction of abnormal identified *modulus* values. Namely (see Fig. 1 a), if $(|\overline{P_1a}|<\delta$ or $P_4 \notin R$ and $|\overline{P_3a}|<(1-\delta)|\overline{P_1a}|)$ then apply $a = 0.5\,(P_1+P_3)$.

In Fig. 1c some results obtained with Landau's method and with the described correction steps are shown.

THE LOCALISATION METHOD

The identification of elliptical regions is performed upon a path search algorithm whose primary inputs are a set of membership coefficients obtained from a neural network. Several results can be seen in Fig. 2 . The neural network's inputs are derived from a set of geometrical measures, and its output reflects the possibility degree of two distinct *EAS* belonging to the same object. The structure employed for the multilayer feedforward neural network is formed by 6 input, 9 hidden and 1 output neuron, all with a *sigmoid* type activation function. The network was trained using the back-propagation learning algorithm in a modified form including adaptive learning rate (Jacobs, 1988). The training set was composed by 841
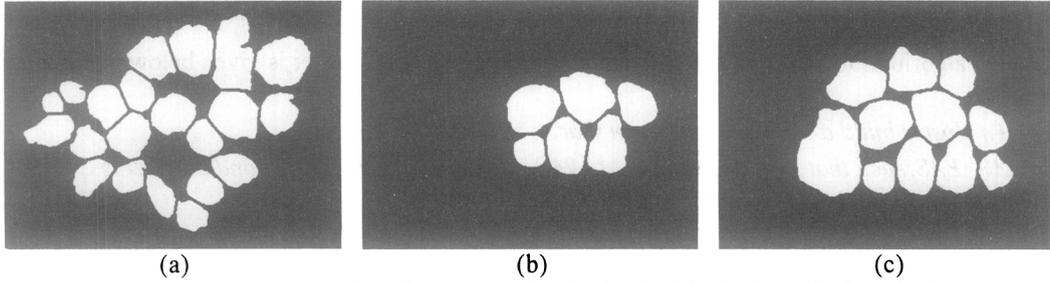
Fig. 2: Lime granule localisation results obtained with the described method.

distinct *EAS*. For training purposes, it is considered that if two *EAS* belong to the same object, then the neural network's output is 0.9, else the output is 0.1. A set of geometrical-based similarity measures are employed as the network's inputs:

Proximity measure: Let EAS_i and EAS_q be two aggregation candidates, their aggregation distance is given by $D^1_{iq}=min\{|\overline{CP_iCP_{q+1}}|, |\overline{CP_{i+1}CP_q}|\}$.

Concentricity measure: the concentricity measure between EAS_i and EAS_q is taken as the distance between their identified centres: $D^2_{iq}=|\overline{a_i a_q}|$

Completeness measure: almost complete arcs tend to aggregate with less complete ones. The completeness measure of EAS_i is taken as $C_i=|\overline{P_1 a}|/|\overline{P_1 P_2}|$. For two aggregation candidates EAS_i and EAS_q, the neural network receives C_i and C_q.

Energy measure: the "energy" resulting from the aggregation between two *EAS* must be inversely proportional to the probability of both *EAS* belonging to the same elliptical object. This measure is taken as ($ord\,(D^1_{iq})$ - returns the order of D^1_{iq} in the ordered set $\{D^1_{ij}\}, j = 1,..., N$):

$$E_{iq} = \left(D^1_{iq} + D^2_{iq}\right)\left(1 + 1/C_i + 1/C_q\right)ln\left(2 + ord\left(D^1_{iq}\right)\right) \quad (2)$$

Curvature similarity measure: for arcs EAS_i and EAS_q, this measure is taken as:

$$Curv_{iq} = max\left(R_i/R_q, R_q/R_i\right) \quad (3)$$

All of these measures are normalised in the [0,1] interval prior to their input to the neural network. After the learning stage, it is considered that two *EAS* (EAS_i and EAS_q) belong to the same elliptical object if the neural network's output $MC_{iq}>0.5$.

Aggregation Path Search with Geometrical-Based Decision Criteria

Although the membership indications obtained from the neural network are very reliable, it may happen that small errors occur (generally less than 0.5%). On the other hand, given a high valued set of *MC* it is not possible to infer from it the aggregation order of the associated *EAS*. To solve this problem a path search method is applied which handles critical boundary situations through neighbourhood analysis and a voting strategy. Aggregation decisions in the path search method are taken on the basis of a set of geometrical-based decision criteria:

Aggregation point criterion: the aggregation between EAS_i and EAS_q must preserve the contour's direction. Therefore, this operation may only be performed between points $\{CP_i, CP_{q+1}\}$ or $\{CP_{i+1}, CP_q\}$. The actual choice is taken upon the minimum value of measure D^1_{iq}.

Centre position criterion: if two *EAS* aggregate together, then it is seen that their estimated centres must lie on the same side of the line segment defined by the contact points obtained with the aggregation point criterion.

Reciprocity criterion: two *EAS* aggregate together, if the aggregation choice is mutual.

Shared adjacency criterion: if EAS_i and EAS_q aggregate together with aggregation points $\{CP_i, CP_{q+1}\}$ or $\{CP_{i+1}, CP_q\}$, then it is seen that, respectively, EAS_{i-1} and EAS_{q+1} or EAS_{i+1} and EAS_{q-1} will also aggregate.

Proximity criterion: aggregation points of sequential *EAS* which belong to the same object tend to be localised at smaller distances from each other than to contact points of other *EAS*. Therefore, the aggregation candidate to EAS_i should be EAS_q if:

$$q = ArgMin_{z=1,...,N \wedge z \neq i}(D^1_{iz}) \tag{4}$$

The detailed algorithm for the path search method for each identified cluster is given below:

For a given cluster build a N×N matrix A such that $A_{ij} = MC_{ij}$, i,j = 1,...,N
Obtain EAS_i, EAS_j such that i,j = $ArgMax_{k,l=1,...,N}$ {A_{ij}}; the initial aggregation candidate set is C={i,j}
While (the absolute maximum in matrix A is greater than 0.5)
*   Extend set C with all EAS_k of the cluster such that A_{lk} >0.5, l∈ C, k = 1,...,N\{i,j}*
*   If the number of EAS identified in C is 2 then*
*   Apply the reciprocity, aggregation point and the centre position criteria*
*   If all criteria are validated then*
*   Both EAS are aggregated and the shared adjacency criterion is applied*
*   Else*
*   The reciprocity criterion is checked for all EAS in C*
*   If all EAS_i, i ∈ C, pass the reciprocity test with respect to all other EAS_j, i ∈ C ∧ j≠i then*
*   For all EAS_i, i ∈ C, the aggregation point, proximity and the centre position criteria are applied*
*   If both criteria are fulfilled then*
*   The all EAS_i, i ∈ C, are aggregated and the shared adjacency criterion applied*
*   Else*
*   A voting strategy is followed, that is, each EAS_i, i ∈ C, votes for all EAS_j, j ∈ C, such that MC_{ij}<0.5.*
*   For each EAS_i with less than 50% of the votes (all the others are discarded form C) the aggregation*
*   point criterion is applied:*
*   If the candidate segment EAS_k of EAS_i has received 0 votes then*
*   If the centre position criterion is verified for EAS_k and EAS_i, the two segments are aggregated*
*   Else it is checked if EAS_{k-1} and EAS_{i+1} or EAS_{k+1} and EAS_{i-1} aggregate together. If this happens*
*   then because of the shared adjacency criterion segments EAS_k of EAS_i must also aggregate*
Obtain the new EAS_i, EAS_j for the initial set C such that i,j = $ArgMax_{k,l=1,...,N}$ {A_{ij}}

CONCLUSIONS

In this paper a new approach to elliptical object localisation is introduced and applied to a lime granule inspection system. The method has proven to be robust, namely, it was able to correct several noisy information introduced in the neural network's output during the test procedure. Given the noise rejection ability of the path search method and the reduced membership degree error obtained by the neural network, these results may suggest the application of this method to other problems of different areas.

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