Invariant Recognition of Rectangular Biscuits with Fuzzy Moment Descriptors, Flawed Pieces Detection

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Abstract

In this paper a new approach for invariant recognition of broken rectangular biscuits is proposed using fuzzy membership-distance products, called fuzzy moment descriptors. The existing methods for recognition of flawed rectangular biscuits are mostly based on Hough transform. However these methods are prone to error due to noise and/or variation in illumination. Fuzzy moment descriptors are less sensitive to noise thus making it an effective approach and invariant to the above stray external disturbances. Further, the normalization and sorting of the moment vectors make it a size and rotation invariant recognition process .In earlier studies fuzzy moment descriptors has successfully been applied in image matching problem. In this paper the algorithm is applied in recognition of flawed and non-flawed rectangular biscuits. In general the proposed algorithm has potential applications in industrial quality control.

Keywords: Fuzzy moment descriptors, Euclidean distance, Edge detection, Flawed biscuits detection.

1. INTRODUCTION

The problem of pattern recognition has been studied extensively in different literatures in different domain. Invariant pattern recognition in Hough space [1]-[4] has already been addressed by Krishnapuram et al [5], and by Sinha et al [6], none of these two works includes the treatment of size-scaling. Authors in [5] and [6] use convolution in 9-space to achieve the rotational registration between sample objects and the templates, an additional processing is then necessary to determine the translational correspondence. The use of a pre-defined standard position in Hough space along with Distance-Discriminator Neural Neurons to achieve invariant pattern recognition has been addressed by Montenegro et al [7].In that the distance between a template and a sample vector gives the corresponding likeliness degree. If several objects appear simultaneously in image space a preprocessing is necessary to single out individual objects by some of the broadly known labeling [8] technique. The authors in [9] have applied Hough transform in contour identification for object identification. In [10]-[11], the author proposed the geometric transformation invariant pattern recognition in Hough space for polygonal shaped objects. In [12] the author proposed the algorithm for flawed biscuits detection in Hough space. In their method the recognition process is done entirely in the Hough space. The same algorithm has been applied in recognition of rectangular chocolates [13] and metallic corners-fasteners [14].In [15] the authors proposed a technique for extracting rectangular shape objects from real color images using a combination of global contour based line segment detection and a Markov random field (MRF) model.

In this paper we proposed rectangular broken biscuit detection problem using Fuzzy moment descriptor. Fuzzy logic [16] which has proved itself successful in matching of inexact data can equally be used for inexact matching of close image attributes. In [17] the authors introduced the concept of fuzzy moment descriptor technique in invariant recognition of gray image and successfully applied in face recognition problem. The authors used the Euclidean distance of a reference image and the test images as the metric for recognition. The test image that has least Euclidean distance is taken as the best matched image. The authors in [18] proposed a new method for image registration based on Nonsubsampled Contourlet Transform (NCST) for feature extraction and the matching of a test image with a reference image is achieved using Zernike moments. This approach can be extended for shape matching and object classification. However our present work is mainly focused on the used Fuzzy moment descriptor proposed in [17].

In this technique an input gray image has been partitioned into n^2 non overlapped blocks of equal dimensions. Blocks containing region of edge is then identified The degree of membership of a given block to contain edges is measured subsequently with the help of a few pre-estimated image parameters like average gradient, variance and the difference of the maximum and the minimum of gradients. Fuzzy moment which informally means the membership-distance product of a block b[i, w] with respect to a block b[j, k],is computed for all $1 \le i, w, j, k \le n$. A feature called ‘sum of fuzzy moments’ that keeps track of the image characteristics and their relative distances is used as image descriptor. We used Euclidean distance measure to determine the distance between the image descriptors of a reference image and a test image. Then we set a threshold value of the Euclidean distance for separating flawed and non-flawed rectangular biscuits.

The remainder of the paper is outlined as follows. Section 2 describes the estimation of fuzzy membership distribution of a given block to contain edge. A method for computing the fuzzy moments and a method for constructing the image descriptors are presented in section3.The algorithm for the invariant recognition of rectangular biscuits is described in section 4.The simulation result is presented in section 5 and section 6 concludes the paper.

2. IMAGE FEATURES AND THEIR MEMBERSHIP DISTRIBUTIONS

This section describes briefly the image features used in the proposed technique and their fuzzy membership distributions.

Definition 2.1 An edge is a contour of pixels of large gradient with respect to its neighbors in an image.

Definition 2.2 Fuzzy membership distribution $\mu_Y(x)$ denotes the degree of membership of a variable x to belong to Y, where Y is a subset of a universal set U.

Definition 2.3 The gradient (Gonzalez and Wintz, 1993) at a pixel (x, y) in an image is estimated by taking the square root of the sum of difference of gray levels of the neighboring pixels with respect to pixel (x, y).

Definition 2.4 The gradient difference (G_{diff}) within a partitioned block is defined as the difference of maximum and minimum gradient values in that block.

Definition 2.5 The gradient average (G_{avg}) within a block is defined as the average of the gradient of all pixels within that block.

Definition 2.6 The variance (σ^2) of gradient is defined as the arithmetic mean of square of deviation from mean. It is expressed formally as

$$\sigma^2 = \sum (G - G_{avg})^2 P(G)$$

Where G denotes the gradient values at pixels, and P(G) represents the probability of the particular gradient G in that block.

2.1 Fuzzy Membership Distributions

Once the features of the partitioned blocks in an image are estimated following the above definitions, the same features may be used for the estimation of membership value of a block containing Edge.

Consider when a block contains edge, the gradient in such blocks will have non-zero values only on the edges. So there must be a small positive average gradient of the pixels in these blocks. Consequently, σ^2 should be a small positive number. we may thus generalize that when σ^2 is close to zero but positive, the membership of a block b_{ij} to contain edge is high, and low otherwise, based on these intuitive assumptions, we presumed the membership curves $\mu(b_{jk})$ = 1– exp(bx^2), b > 0. The exact value of b can be evaluated by employing genetic algorithms (Man et al., 1999). It may be noted that 1– exp ($-bx^2$) has a zero value at $x = \sigma^2 = 0$ and approaches unity as $x = \sigma^2 \rightarrow \infty$. The square of x, ($x^2$) represents the faster rate of growth of the membership curve 1– exp ($-bx^2$).

Analogously, the average gradient G_{avg} of a block b_{ij} containing only edge is large. Thus, the membership of a block b_{ij} to contain edge will be high, when G_{avg} is large. This phenomena can be represented by the membership function 1- exp ($-\alpha x$), $\alpha > 0$. The selection of the membership function for edge w.r.t. G_{diff} directly follows from the previous discussion.

TABLE 1: Membership functions for features

Parameter	Edge membership
G_{avg}	$1- e^{-8x}$
G_{diff}	1– exp ($-bx^2$) b > 0
σ^2	1– exp ($-bx^2$) b > 0

The membership values of a block b [j,k] containing edge can be easily estimated if the parameters and the membership curves are known. The fuzzy production rules, described below, are subsequently used to estimate the degree of membership of a block b [j, k] to contain edge by taking into account the effect of the parameters.

2.2 Fuzzy production rules

A fuzzy production rule is an if-then relationship representing a piece of knowledge in a given problem domain. For the estimation of fuzzy memberships of a block b [j, k] to contain, say, edge, we need to obtain the composite membership value from their individual parametric values. The if-then rules represent logical mapping functions from the individual parametric memberships to the composite membership of a block containing edge. The production rule PR1 is a typical example of the above concept.

PR1: IF ($G_{avg} > 0.142$) AND
($G_{diff} > 0.707$) AND
($\sigma^2 \approx 1.0$)
THEN (the block contains edges).

Let us assume that the G_{avg}, G_{diff} and σ^2 for a given partitioned block have found to be 0.149, 0.8 and 0.9, respectively. The μ_{edge} (b_{jk}) now can be estimated first by obtaining the membership values μ_{edge} (b_{jk}) w.r.t. G_{avg}, G_{diff} and σ^2, respectively by consulting the membership curves and then by applying the fuzzy AND (minimum) operator over these membership values. The single valued membership, thus obtained, describes the degree of membership of the block b[j,k] to contain edge.

3. FUZZY MOMENT DESCRIPTORS

In this section we define fuzzy moments and evaluate image descriptors based on those moments. A few definitions, which will be required to understand the concept, are defined below.

Definition 3.1. *Fuzzy edge moment* $\left[M_{iw}^{jk}\right]_{edge}$ is estimated by taking the product of the membership value $\mu_{edge}(b_{jk})$ (of containing edge in the block $b[j,k]$) and normalized Euclidean distance $d_{iw,jk}$ of the block $b[j,k]$ w.r.t. $b[i,w]$. Formally,

$$\left[M_{iw}^{jk}\right]_{edge} = d_{iw,jk} \times \mu_{edge}(b_{jk}) \tag{3.1}$$

Definition 3.2. *The fuzzy sum of moments* (FSM), for edge S_{iw}, w.r.t. block b[i,w] is defined as the sum of edge moments of the blocks where edge membership is the highest among all other membership values.
Formally,

$$S_{iw} = \sum_{\exists jk} d_{iw,jk} \times \mu_{edge}(b_{jk}) \tag{3.2}$$

Where $\mu_{edge}(b_{jk}) \geq \mathrm{Max}\left[\mu_x(b_{jk})\right], \ x \ \varepsilon$ set of features

After the estimation of the fuzzy membership values for edges, the predominant membership value for each block and the predominant feature are saved. The FSM with respect to the predominant features are evaluated for each block in the image. Each set of FSM is stored in a one-dimensional array and is sorted in a descending order. These sorted vectors are used as descriptors for the image.

For matching a reference image with a set of input images, one has to estimate the image descriptors for the reference and the input images. For our recognition process we used a non broken biscuit as the reference image. The matching of images requires estimation of Euclidean distance between the reference image with respect to all other input images. The measure of the distance between descriptors of two images is evident from Definition 3.3.

Definition 3.3 The Euclidean distance $[E_{i,j}]_k$, between the corresponding two kth sorted FSM descriptor vectors V_i and V_j of two images I and j of respective dimensions (n×1) and (m×1) is estimated first by ignoring the last (n – m) elements of the first array, where n > m and then taking the sum of square of the elemental differences of the second array with respect to the modified first array having m elements.

Definition 3.4 The measure of distance between two images, hereafter called image distance, is estimated by taking exhaustively the Euclidean distance between each of the two similar descriptor vectors of the two images and then by taking the weighted sum of these Euclidean distances.
Formally, the distance D_{ry} between a reference image r and an image y is defined as

$$D_{ry} = \sum \beta_k \times [E_{ij}]_k \tag{3.3}$$

Where the suffix i and j in $[E_{ij}]_k$ correspond to the set of vectors V_i for image r and V_j for image y.

In our technique of flawed pieces detection of rectangular biscuits we estimate the image distance D_{ry} where y Є the set of input images and r denotes the reference image. The image for which the image distance D_{ry} is larger than a predefined threshold belongs to flawed pieces otherwise the biscuit is non-broken.

4. ALGORITHM

In this section the algorithm used in invariant recognition of rectangular biscuits is presented. The algorithm requires a reference image which is a non-broken biscuit image and a set of input images for recognition process. Here all the images to the algorithm are supplied after the images passes through an edge detector. For recognition of rectangular biscuits only the edge information of the image is sufficient. The edge detection may be performed using Sobel edge detector or Cany edge detector. For our problem we have used a simple Sobel edge detector.

The major steps for the process is as depicted in figure 4.1

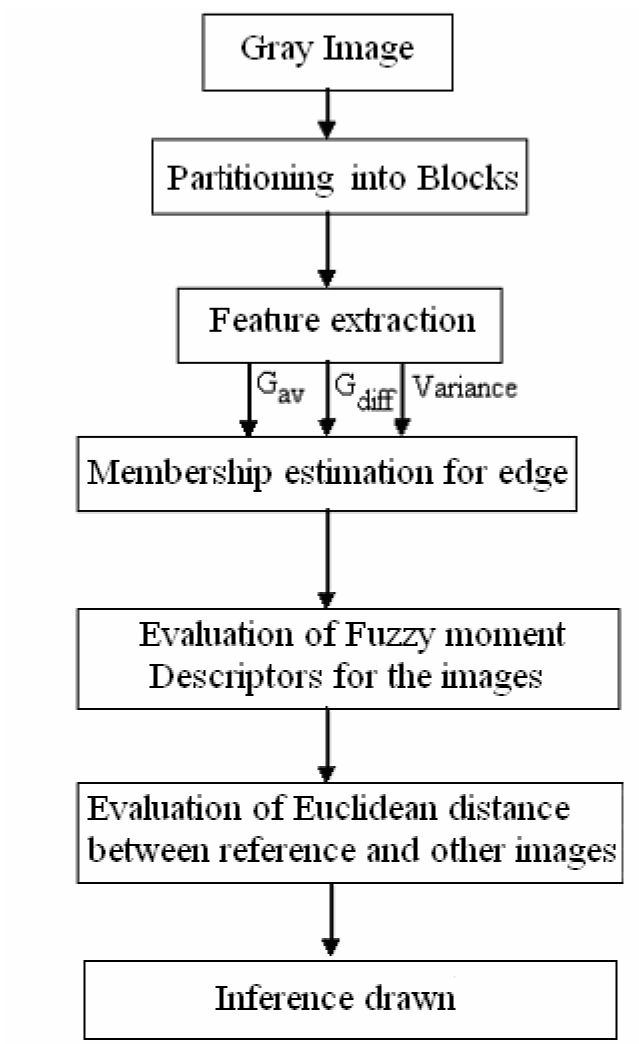

Figure 1: Basic steps involved in the recognition process

In order to keep the matching process free from size and rotational variance, the following strategies have been adopted.

I. Euclidean distances between each two blocks of an image used for estimation of fuzzy moments are normalized with respect to the image itself.
II. the descriptor vectors are sorted so as to keep the blocks with most predominant features at the beginning of the array, which only participate subsequently in the matching process is free from rotational variance of the reference image

5. SIMULATION RESULTS

To study the effectiveness of the proposed algorithm we consider computer generated images as shown in figure 2. These computer synthesized images directly follows from [12]. In the figure 2, the image ref is the reference image which is a non-broken rectangular biscuit and the images r2 – r12 are taken as the input test images

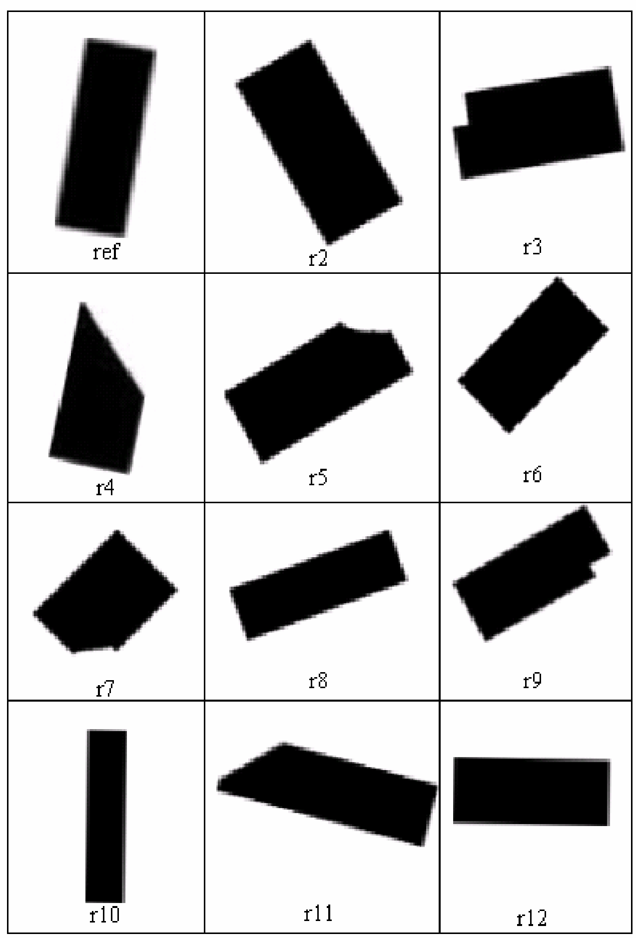

Figure 2: Computer generated biscuit images

Table 2: Euclidean Distance between the reference & the test input images

Test images	Euclidean distance
r2	0.244295
r3	1.850987
r4	3.645934
r5	1.711132
r6	0.462434
r7	2.635301
r8	0.254587
r9	1.538170
r10	0.430162
r11	1.517850
r12	0.142401

From table 2 we can observe that if the test input images are unbroken biscuits then the Euclidean distance between the input images and the reference image are small whereas for broken biscuits (flawed pieces) the Euclidean distance is high. Therefore using the Euclidean distance as the metric we can separate broken rectangular biscuits from unbroken rectangular biscuits. We can draw an inference from the Euclidean metric that, if the Euclidean distance is greater than a predefined threshold the biscuit is a broken biscuits otherwise unbroken. The choice of the threshold is very critical in the successful detection of broken biscuits. There may be many methods for designing the threshold value. Presently we choose the threshold intuitively based on the database in performing the simulations. The test input images r2, r6, r8, r10 and r12 are unbroken biscuits of different size and orientations (figure 2) while the remaining biscuits are flawed pieces. It can be observed from table 2 that for unbroken biscuits the Euclidean distance is below 1 and for flawed pieces it is greater than 1. For simulation using the above set of images we choose the value of the Euclidean distance threshold to be equal to 1. For set the of test input images this threshold perfectly works. However this may not be an ideal way of designing the threshold. But if the database is very large then the intuitive way of choosing threshold may produce result with less error. The results may be less satisfactory compared to the method proposed in [12] however their algorithm will fail to recognize the image r10 and r12 in figure 2 as it cannot be applied to Horizontally and vertically align images. Our proposed algorithm is more robust compared to algorithm based on Hough transform[12].

6. CONCLUSION

In this paper we have shown that fuzzy moment descriptor can be used in invariant recognition of rectangular biscuits with detection of flawed biscuits pieces detection. The proposed technique is not limited to only rectangular objects; it can be applied to appropriate pattern recognition problem also. The proposed technique is less sensitive to external noise as compared to the technique using Hough space. But the intuitive way of choosing the threshold may not be an ideal. The use of neural networks or any optimization technique in choosing the threshold is considered as future aspect in continuation of this work.

7. REFERENCES

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