

A Novel Algorithm for Grey Level Co-occurrence Matrix Computation in Real Time Biomedical Image Analysis

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ABSTRACT

Commonly, MRI images appear in grey-level form. However, the tonal intensity is not sufficient to describe each image texture class. The extraction of textural features is very important in the process of image segmentation. The most common class of textural features is based on the grey-level co-occurrence matrix (GLCM) [4]. The major drawback in the use of GLCM to calculate texture features for image segmentation is that it is very intensive computationally. Although, GLC matrices are generally sparse, most of the calculations are done over unnecessary zero probabilities. To deal with this problem, [5] suggested the use of a grey level co-occurrence linked list (GLCLL) for storing the non-zero probabilities. Other techniques have been suggested as faster alternatives to GLCM calculation [1, 2, 3]. In this paper, we propose a method for image segmentation based on features computed from GLCM and k-means clustering. Six of the most common Haralick's features are calculated [4]. Moreover, two new statistical features are introduced. For the GLCM calculation phase, we introduce a novel algorithm called grey level co-occurrence indexed list (GLCIL) for fast element access and computational time reduction. Finally, the k-means clustering algorithm is used for texture segmentation.

A GLCM is defined as the joint probability of occurrence of two grey level values at a given offset (in terms of both distance and orientation). It is computed over $n \times m$ image I at a distance d and an orientation θ , as:

$$C_{(d,\theta)} = \sum_{x=1}^n \sum_{y=1}^m \begin{cases} 1, & \text{if } I(x, y) = i \text{ and } I(x', y') = j \\ 0, & \text{otherwise} \end{cases}$$

where x' and y' are calculated from x , y , d and θ , $1 \leq x' \leq n$, $1 \leq y' \leq m$ and $1 \leq i, j \leq q - 1$. The value of q corresponds to the number of different grey levels in I , that is, its quantization levels. The GLCM is a square matrix of dimension q . According to this definition, each element $C_{(d,\theta)}(i, j)$ in the GLCM represents the number of occurrences of the grey-level pair (i, j) in I . These values can be converted to probabilities and, in this way, element $C_{(d,\theta)}(i, j)$ indicates the probability of the grey-level pair (i, j) occur in I . The dimension of the GLCM is directly related to its computational drawbacks for features calculation. In fact, a higher GLCM dimension leads to higher computational requirements. This results in an excessive amount of computation for image segmentation in many types of medical images, particularly in MRI, where there is a large number of intensity levels. Fortunately, some greyscale images may have their quantization levels reduced without degrading the quality of textural information. In these cases, quantization is a simple way of decreasing the dimensionality of GLCM. However, in medical images, this could mask the segmentation results and even suppress the presence of important

characteristics (such as tumour seeds). The new approach presented here speeds up the calculation of textural features without affecting the results of the segmentation. All features and values are precisely the same as in the full GLCM case. The proposed methodology is based on the grey-level co occurrence indexed list for fast element access. This highly optimizes this step in the implemented system. It uses a $n' \times n'$ sliding window for co-occurrence matrix calculation and subsequent features extraction. For each input image pixel p , the window is positioned so that its first cell matches the p position on the image. Co-occurrence information is calculated inside the window and associated to pixel p . Features are extracted from these co-occurrence matrices which are also associated to p . Two other algorithms were also implemented in Java for comparison purposes, i.e., the GLCM and the non sorted version of the GLCLL. Figure 1 shows the performance of GLCIL as compared to GLCM. It is evident that GLCIL is more computationally efficient when the number of grey levels is large; however computational savings reduce with the increase in window size. Figure 2 demonstrates the superior computational savings of GLCIL when compared to GLCLL. Our approach (GLCIL) has been tested on MRI images used in virtual colonoscopy procedures, as shown in Figure 3; they are characterised by a large number of grey levels and typically require small window sizes.

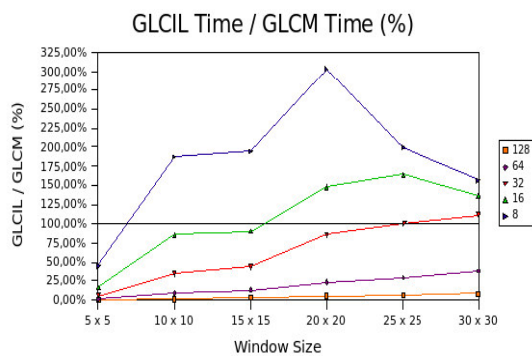


Figure 1: GLCIL vs GLCM [4]

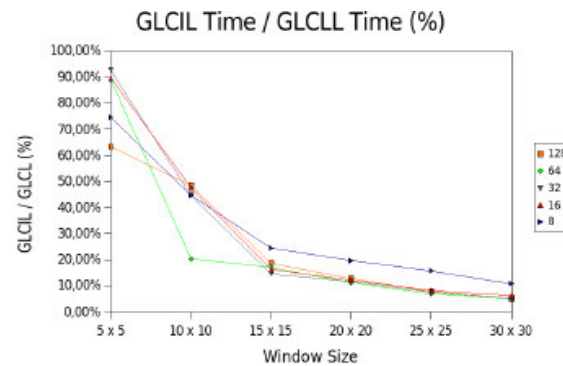


Figure 2: GLCIL vs GLCLL [5]

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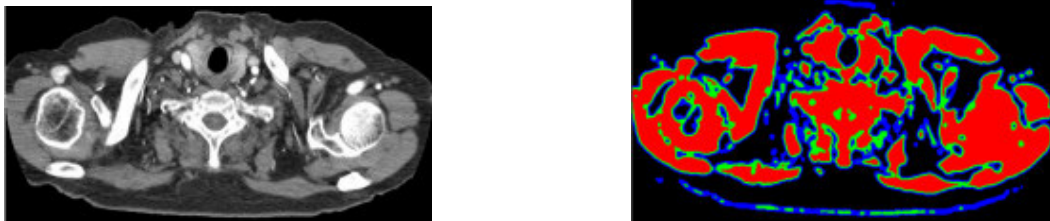


Figure 3: Left: MRI (colonoscopy image) and Right: GLCIL segmentation results.