

應用廣義加權平均集成運算於影像邊緣偵測

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摘要

本論文主要包含兩大部分。第一部分運用區間值模糊關係的概念，在任意一張灰階影像中建構出足以顯現 3×3 視窗內中心像素和其8鄰域像素強度值變化之模糊邊緣影像；第二部分，我們利用一組廣義加權平均運算元，針對中心像素值進行加權平均差值集成運算，此運算可實現第一部分之模糊邊緣影像，然後經由門檻值作用以獲得邊緣偵測結果。另外，我們也經由最速梯度演算法的概念進行平均集成參數值的學習，並提升邊緣偵測正確率，意即我們已成功開發出一套能自動學習參數之影像邊緣偵測方法。而從八張添加隨機雜訊的灰階合成影像測試結果顯示，整合區間值模糊關係的技術與像素值加權平均集成演算法，將產生更為強健的邊緣偵測響應。最後，藉由以最佳邊緣偵測運算參數於自然影像邊緣偵測的應用，我們發現其效果將更勝於著名的Canny邊緣偵測器。

Applying Weighted Generalized Mean Aggregation to Edge Detection of Images

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ABSTRACT

This thesis consists of two parts. The first part utilizes the concept of interval-valued fuzzy relations in any grayscale image to construct a fuzzy edge image. This fuzzy image shows the changes in intensity values between a 3×3 window central pixel and its eight neighbor pixels. In the second part, we employ a set of weighted generalized mean operands, and perform the weighted mean aggregation calculation for the central pixels. The calculation realizes the fuzzy edge images of the first part. Then, we obtain the image edge maps through a thresholding operation. Moreover, we make use of the steepest gradient method to learn the mean aggregation parameters, which in terms increase the edge detection accuracy. Namely, we have developed an automatic parameter learning mechanism for edge detection. By the testing results of eight grayscale synthetic images mixed with random noises, we have shown that the integration of interval-valued fuzzy relation technique with the weighted mean aggregation algorithm will lead to a more robust response for image edge detection. Finally, by applying the best parameters of edge detection to the edge detection of natural images, we have found that the effect is better compared to the popular Canny edge detector.

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