REMOVING THE TEXTURE FEATURE RESPONSE TO OBJECT BOUNDARIES

Padraig Corcoran and Adam Winstanley
National Centre for Geocomputation, John Hume Building, National University of Ireland Maynooth, Ireland

Keywords: Segmentation, Texture Boundary Response, Gabor Filters.

Abstract: Texture is a spatial property and thus any features used to describe it must be calculated within a neighbourhood. This process of integrating information over a neighbourhood leads to what we will refer to as the texture boundary response problem, where an unwanted response is observed at object boundaries. This response is due to features being extracted from a mixture of textures and/or an intensity edge between objects. If segmentation is performed using these raw features this will lead to the generation of unwanted classes along object boundaries. To overcome this, post processing of feature images must be performed to remove this response before a classification algorithm can be applied. To date this problem has received little attention with no evaluation of the alternative solutions available in the literature of which we are aware. In this work we perform an evaluation of known solutions to the boundary response problem and discover separable median filtering to be the current best choice. An in depth evaluation of the separable median filtering approach shows that it fails to remove certain parts or types of object boundary response. To overcome this failing we propose two alternative techniques which involve either post processing of the separable median filtered result or an alternative filtering technique.

1 INTRODUCTION

Segmentation is probably one of the most important and fundamental tasks in computer vision. Despite the vast literature and literally hundreds of algorithms, the problem of segmentation still remains unsolved (Pantofaru and Hebert, 2005). If each object in a given scene was of uniform intensity then segmentation would be trivial but this is not the case, a given scene will not only contain regions of uniform intensity but also regions of uniform texture. Attempting segmentation using solely intensity features ignoring the presence of texture will lead to over segmentation due to false edges generated by the intensity variation within texture. A common approach to reduce the number of false edges is to smooth the image prior to segmentation in an attempt to remove these false edges due to texture while maintaining edges due to object boundaries (Deng and Liu, 2003). When working with intensity based images, a large number of objects will have similar average intensity values, thus smoothing will not only remove edges due to texture but also edges due to object boundaries leading to under segmentation. Therefore when attempting to derive accurate segmentation of intensity images it is important to model the texture within these images and integrate it with intensity features in an intelligent manner, so boundaries between objects which have similar average intensity values but different textures can be detected (Corcoran and Winstanley, 2006).

In this paper we focus on the task of extracting useful texture features from a given image. Texture is a spatial property and therefore any features used to describe it must be calculated over a neighbourhood. A points neighbourhood which is located across an object boundary may contain two or more different textures and/or a large intensity edge giving an unwanted response along the boundary which we call the texture boundary response. If segmentation is derived using these raw features false segments will appear along these objects boundaries. To overcome this failing it is common to apply some form of post-processing to the raw feature images removing the unwanted response before segmentation is attempted. Although this is a necessary step in any texture feature extraction process it has received little attention and thus we believe is poorly understood

Corcoran P. and Winstanley A. (2007).
REMOVING THE TEXTURE FEATURE RESPONSE TO OBJECT BOUNDARIES.
In *Proceedings of the Second International Conference on Computer Vision Theory and Applications - IFP/IA*, pages 363-368

with no evaluation of existing solutions available in literature, of which we are aware.

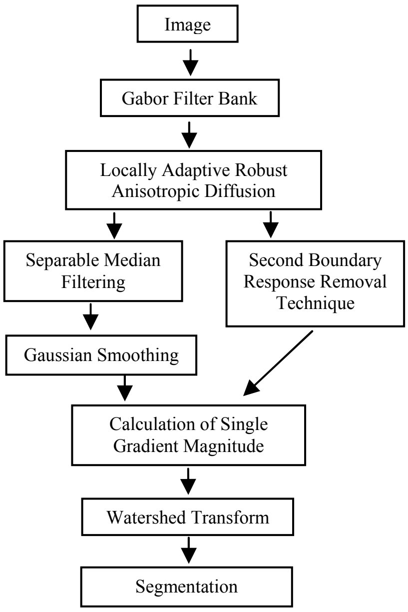


Figure1: Schematic of overall system within which each boundary response removal technique is evaluated.

In an effort to provide a better understanding of the boundary response problem, the different types of responses which may occur in texture feature images are described. We evaluate all know solutions to remove these with separable median filtering being the most accurate. An in-depth evaluation of separable median filtering shows it fails to remove certain types or parts of object boundary responses. To overcome this we propose two new techniques. The first operates as a post processing technique to the separable median filtering and the second is a separate filtering technique. Evaluation is performed by judging the effectiveness of the boundary response removal techniques with respect to the improvement in segmentation achieved once they have been applied. A schematic of the system within which these techniques are implemented is shown in Figure 1.

In the second section of this paper we present the texture boundary response problem in more detail and evaluate existing solutions to the problem. In the third section we show the different types of object boundary responses which may occur and the result after median filtering has been applied. We detail alternative solutions to removing these boundary responses which overcome the failings of previous solutions. Results of our proposed techniques are presented in section 4. Finally, in section 5 we draw conclusions and discuss future work.

2 TEXTURE BOUNDARY RESPONSE PROBLEM AND EXISTING SOLUTIONS

A texture boundary response can be either negative or positive relative to neighbourhood values. An image taken from the Berkeley segmentation dataset (Martin, Fowlkes et al., 2001) is shown in Figure 2. Features of a low central spatial frequency with high spatial resolution extracted from this image using a Gabor filter (Clausi and Jernigan, 2000) is shown in Figure 3. This image displays a negative response at object boundaries relative to neighbourhood values.

Figure 2: Example of image taken from the Berkeley segmentation dataset.

This negative response is due to the fact that the Gabor filter in this case is designed to respond to low spatial frequency. The image contains a number of nearly uniform intensity areas and thus this specific Gabor filter will respond strongly to such areas but will not respond to areas of high spatial frequency such as an object boundary which has a large intensity edge and therefore high spatial frequency. The opposite of this effect can also occur where a positive response at object boundaries relative to neighbourhood values is displayed. A number of authors are under the impression that the texture boundary response is always a response that is greater then its neighbouring values (Kruizinga and Petkov, 1999; Grigorescu, Petkov et al., 2002; Jobanputra and Clausi, 2006) but this is not the case.

Within the literature there exist a number of solutions that attempt to tackle the object boundary response problem. We will now review and evaluate each of these in turn. The first technique we discuss was initially employed in (Shao and Forstner, 1994) and later used in (Martin, Fowlkes et al., 2004). This solution is not applied to the actual feature space. First the gradient magnitude of a given feature image is calculated which gives a double peak effect at all boundary locations where the texture feature extraction responds positively or negatively with respect to its neighbourhood. This gradient magnitude image is then smoothed with a large enough Gaussian kernel converting the two peaks into a single peak. Since this technique does not try to eliminate the response to object boundaries both intensity and texture boundaries will be detected. This would be an undesirable property if the goal of an algorithm is to detect only texture boundaries with the aim of later integrating with a model which detects only intensity boundaries.

Figure 3: Features extracted from Figure 2 exhibit the boundary response problem.

A recent paper by Jobanputra (Jobanputra and Clausi, 2006) tackles the boundary response problem by choosing a set of texture features which give a smoothed step response at object boundaries for a given dataset. If segmentation is then run at a high enough scale the boundary response values will be assigned to classes either side of the boundary. This approach is not data and model independent and it is difficult to prove that a given feature extraction algorithm will always give a smoothed step edge at object boundaries for a given data type. Also since we may only choose features which give a smoothed step edge this limits the texture features which may be used therefore reducing class separability

Another approach to tackle the boundary response problem is to perform separable 2-D median filtering of the feature images. Median filtering is a smoothing technique which can preserve discontinuities in a step function (Lim, 1989). It is robust to noise or outliers having a size less then half the size of the median filter used. Thus any median filter used to remove object boundary responses must be at least twice the width of any object boundary response if it is to be removed.

From the above discussion, the separable median filtering approach of (O'Callaghan and Bull 2005) represents the current best solution to the boundary response problem. It is data and model independent, can remove boundary responses that are either negative or positive in relation to neighbourhood values and also removes responses which are due to a pure intensity edge. In the following section we will perform a detailed evaluation of the different types of boundary responses that may occur and the results after this separable median filtering approach has been applied in an attempt remove them.

3 TYPES OF OBJECT BOUNDARY RESPONSES AND MEDIAN FILTERING

When a window extracting texture features moves across the boundary between two objects one of a number of responses may occur. The first is a response which is similar to a smoothed step edge as shown in Figure 4(a). The result after applying a median filter with greater extent then twice the width of the boundary response is shown in Figure 4(b). Median filtering fails to remove such a boundary response.

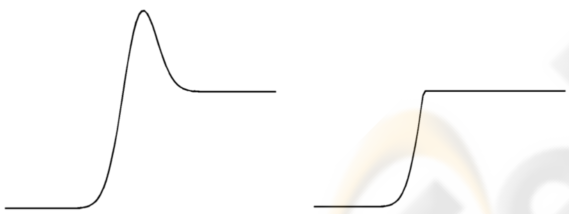
(a) (b)

Figure 4: A smoothed step like boundary response is shown in (a) and the result post median filtering in (b).

A second type of boundary response which may occur is a response which is positive with respect to neighbouring values. An example such a response is shown in Figure 5(a) and the result after applying a median filter with greater extent than twice the width of the boundary response is shown in Figure 5(b). Although median filtering removes the part of the boundary response which is positive with respect to all neighbouring values, it fails to remove the section of the response which resembles a smoothed step edge.

Other forms of boundary response which may occur include a response which is negative with respect to neighbouring values. No response to a boundary between two objects which have similar texture properties and respond equally to the texture feature extraction algorithm. This is represented in two dimensions by a straight horizontal line. A positive or negative response relative to similar neighbouring values on both sides, this is represented in two dimensions by a straight horizontal line containing a region of relative positive or negative values. A pure intensity boundary usually results in this form of boundary response.

In all the above forms of texture boundary responses, separable median filtering will remove the section of the response which is positive or negative with respect to neighbouring values on both sides. It will fail to remove a section of the response if it contains values which are between the two levels on either side as shown in Figures 4 and 5. This property of median filtering presents the problem of how to perform segmentation using these features without the generation of unwanted segments along object boundaries, given that separable median filtering will not remove the entire boundary response. To achieve this we propose two solutions, the first involves post-processing of the median filtered images, and the second involves a separate filtering technique. We will discuss each of these in turn now.



(a) (b)

Figure 5: A boundary response which is positive with respect to neighbouring values is shown in (a) and the result post median filtering in (b).

The first approach we propose is to perform segmentation at a greater spatial scale then the extent of the sections of boundary response which remain post separable median filtering. The boundary responses remaining after separable median filtering will in general be significantly smaller then the scale of the window used in texture feature extraction. Also the section of the boundary response remaining will already resemble a step edge at a higher scale due to the fact that it will contain continuously increasing or decreasing values. In fact it could be described as a smooth step edge containing some noise. These two facts permit the use of smoothing with a small Gaussian kernel relative to the scale used in feature extraction. The effect is to produce features represented at a spatial scale where unwanted segments along boundaries will not appear in the segmentation result. One drawback of this method is that Gaussian smoothing will always introduce a loss in boundary localization. Figure 6 (a) shows the result of this technique applied to Figure 3. An alternative approach would be to perform the segmentation algorithm at a higher scale, but this would lead to under-segmentation if all boundaries did have similar absolute differences.

(a) (b)

Figure 6: The results of both texture boundary response removal techniques.

The second approach we propose to tackle the boundary response problem involves the processing of the feature image with a new filtering technique. This technique takes as input two parameters; t the threshold size which is the maximum size of an object for it to be considered an object boundary response and θ the orientation of the texture feature extraction algorithm. We first detail how this method is implemented in 1-D and then extend it to 2-D. The 1-D method is implemented in two steps:

1) A 1-dimensional context window of length t is aligned around a given point of interest where the window contains that point and minimizes the sum of absolute difference between that point and the two boundary points of the window. This step aligns the window for a given point with the neighbourhood to which it is most similar.
2) Then the point of interest is assigned the boundary value of this window from which it is most dissimilar.

These two steps are performed on every point in the dataset. All boundary responses will be replaced with step edges where the boundary responses cross the midway point between the two uniform regions on either side. If the two uniform regions either side of a boundary response have values of 0 and 1, the step edge returned by the algorithm will be located where the boundary response crosses the value of 0.5. We are working on the assumption that this is the optimal point where the step edge should occur. An illustration of this process applied to a data point in a one-dimensional dataset is shown in Figures 7. The result of the algorithm applied to Figure 4(a) and Figure 5(a) is shown in Figure 8(a) and (b) respectively.

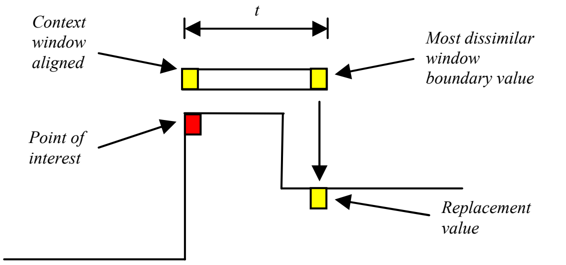


Figure 7: Proposed texture boundary response removal technique is performed to a point of interest which is a member of a boundary response.

To extend this technique to two dimensions we first apply the 1-D method in a direction parallel to the direction of the feature extraction and then again in a direction orthogonal to this. An Example of this method applied to the Gabor feature image in Figure 3 is shown in Figure 6(b). We can see that this method removes the boundary responses while maintaining boundary localization and only suffers a small drop in image detail.

(a) (b)

Figure 8: Results of the second proposed algorithm for removing boundary responses applied to Figure 4(a) and Figure 5(a) shown in (a) and (b) respectively.

Following feature extraction all feature images are smoothed by a non-linear locally adaptive diffusion process. The techniques is similar to that used by Black (Black and Sapiro 1999), except instead of using the local median absolute deviation of grey values we use the local median value of gradient magnitude values. Also we calculate the edges at the same scale as the feature extraction algorithm not at the pixel level as done by Black.

4 TEXTURE BOUNDARY RESPONSE REMOVAL AND EVALUATION

To perform evaluation we judge the effectiveness of our boundary response removal techniques with respect to the improvement in segmentation achieved once the boundary responses have been removed. To perform segmentation we use the marker controlled watershed transform (Soille, 2002). To prevent over-segmentation the gradient magnitude image is first filtered using a marker function, in this case the H-minima transform, to remove all irrelevant minima (Soille, 2002). Figure 9 shows an example of segmentation achieved using this algorithm.

Evaluation is performed using data from the Berkeley segmentation dataset (Martin, Fowlkes et al., 2001). For each of the images in this dataset 5 to 10 ground truths from different individuals are available. For quantitative comparison of a single segmentation result to a set of corresponding ground truths the Normalized Probabilistic Rand (NPR) index is used (Unnikrishnan, Pantofaru et al., 2005). This index can be used to measure the relative accuracy for various algorithms at producing a useful segmentation for a given image. The greater the index score, the greater the performance.

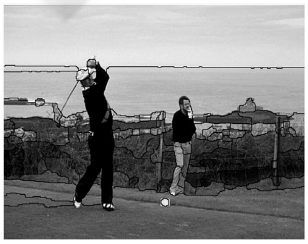


Figure 9: Segmentation performed by applying the watershed transform.

For evaluation 200 images from the Berkeley dataset are used and this is split into 100 training and 100 test images. Using the training set, the scale of segmentation is optimized by varying the h-minima value. The separable Median filtering of (O'Callaghan and Bull, 2005) followed by smoothing approach slightly outperforms the second technique on the training dataset.

Using both boundary response removal techniques optimized on the training dataset we evaluate on the test dataset. On the 100 images in the test dataset the separable median filtering followed by smoothing technique achieved an average NPR index value of 0.48, while the second boundary response removal technique received an average score of 0.44. The slight decrease in performance for the second technique relative to the first is probably due to the fact that the second technique is not as robust to noise as the first.

5 CONCLUSIONS

The aim of this paper was to provide researchers in the area of segmentation with a better understanding of the texture boundary response problem. Prior to this we could not find any work stating the different forms of boundary responses which may occur and how best to remove them. An evaluation of all current solutions to removing these texture boundary responses show separable median filtering to be the current best solution. We analyzed the result of applying separable median filtering to all possible boundary responses and showed that it does not remove all or parts of certain responses.

Two alternative techniques which overcome this failing were proposed and evaluated. The first technique is robust to noise but suffers from a loss in boundary localization. The second technique gives the optimal solution in a noise free environment but is not so robust to noise. Using quantitative evaluation the first approach of extracting edges at a greater scale then the scale of the boundary responses remaining after separable median filtering was shown to perform best. This result does not mean the second technique is redundant. If a feature extraction algorithm which produces noise free images could be found this technique could be used to produce the optimal solution. This is based on the assumption that all boundary responses should be replaced with step edges where the boundary response crosses the midway point between the two uniform regions on either side. Future work will attempt to evaluate whether this is the case.

If useful segmentation is to be produced, both texture and intensity features must be extracted and integrated in an intelligent manner. Future work will also focus on the extraction of useful intensity features and how best to integrate them with the texture features discussed in this paper.

REFERENCES

Black, M. and G. Sapiro (1999). *Edges as outliers: anisotropic smoothing using local image statistics*. International conference on scale-space theories in computer vision, Corfu, Greece. 259- 270.

Clausi, D. A. and M. E. Jernigan (2000). *Designing Gabor filters for optimal texture separability*. Pattern Recognition 33(11): 1835-1849.

Corcoran, P. and A. Winstanley (2006). *Using Texture to Tackle the Problem of Scale in Land-Cover Classification*. International conference on object based image analysis, Salzburg.

Grigorescu, S. E., N. Petkov, et al. (2002). *Comparison of texture features based on Gabor filters*. Image Processing, IEEE Transactions on 11(10): 1160-1167.

Jobanputra, R. and D. A. Clausi (2006). *Preserving boundaries for image texture segmentation using grey level co-occurring probabilities*. Pattern Recognition 39(2): 234-245.

Kruizinga, P. and N. Petkov (1999). *Nonlinear operator for oriented texture*. Image Processing, IEEE Transactions on 8(10): 1395-1407.

Lim, J. S. (1989). *Two-dimensional signal and image processing*, Prentice Hall.

Martin, D., C. Fowlkes, et al. (2001). *A database of human segmented natural images and its applications to evaluating segmentation algorithms and measuring ecological statistics*. International conference on computer vision, Vancouver. 416-423.

Martin, D. R., C. C. Fowlkes, et al. (2004). *Learning to detect natural image boundaries using local brightness, color, and texture cues*. IEEE Transactions on Pattern Analysis and Machine Intelligence 26(5): 530-549.

O'Callaghan, R. J. and D. R. Bull (2005). *Combined morphological-spectral unsupervised image segmentation*. IEEE Transactions on Image Processing 14(1): 49-62.

Pantofaru, C. and M. Hebert (2005). A comparison of image segmentation algorithms. Robotics institute, Carnegie Mellon university, Pittsburgh, PA. Technical Report No. CMU-RI-TR-05-40.

Shao, J. and W. Forstner (1994). *Gabor wavelets for texture edge extraction*. ISPRS commission III symposium on spatial information from digital photogrammetry and computer vision, Munich, Germany. 745-752.

Soille, P. (2002). *Morphological image analysis: principles and applications*, Springer-Verlag Berlin and Heidelberg GmbH & Co. K.

Unnikrishnan, R., C. Pantofaru, et al. (2005). *A measure for objective evaluation of image segmentation algorithms*. IEEE conference on computer vision and pattern recognition, workshop on empirical evaluation methods in c omputer vision, San Diego.