A SHAPE DESCRIPTOR BASED ON SCALE-INVARIANT MULTISCALE FRACTAL DIMENSION

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Keywords: Content-based image retrieval, Shape description, Image foresting transform, Multiscale fractal dimension.

Abstract: This paper proposes a new scale-invariant shape descriptor based on the Multiscale Fractal Dimension (MFD). The MFD is a curve that describes boundary complexity and self-affinity characteristics by obtaining fractal dimension values as function of Euclidean morphologic dilation radii. Using this concept, which guarantees rotation and translation invariance, we introduce a new scale-invariant descriptor that is obtained by selecting a relevant fragment of this curve using a sliding window. The novel shape descriptor is compared with the Multiscale Fractal Dimension and four other shape descriptors. Experimental results demonstrate that the new descriptor is scale-invariant and yields very good results in terms of effectiveness performace when compared with well-known shape descriptors.

1 INTRODUCTION

Image collections have been growing rapidly over the last years (Datta et al., 2008), motivating the research of new indexing and retrieval techniques. Content-based image retrieval (CBIR) is a prominent topic and proposes to index images based on their visual properties. In order to achieve this objective, relevant features (image signatures) must be extracted by low-level descriptors and stored into databases. By defining a distance function to compare different signatures, it is possible to retrieve images that form clusters in the feature space and are assumed to be perceptually similar.

Among the most used low-level features, one can mention colour, texture, shape and spatial location (Liu et al., 2007). Shape is considered an important characteristic and is useful to accurately describe and distinguish segmented objects. Typical properties expected from shape descriptors include invariance to translation, rotation, and scale. Moreover, shape descriptors should be robust to noise, occlusions, and distortions.

Many shape descriptors have been proposed in literature. They are usually classified into two categories: contour-based and region-based (Zhang and Lu, 2004). As their names imply, the former uses only boundary information whilst the latter employs all the image pixels for obtaining a feature vector. Shape descriptors can be further classified between global (in which the contour or region is analysed as a whole) and structural (where smaller primitives are studied separately).

In this paper, a new shape descriptor is proposed, a global contour-based descriptor that exploits fractal theory concepts to describe boundaries. Fractal geometry (Mandelbrot, 1982) is a field of mathematics that aims to analyze complex shapes. This theory has been widely used in the image processing literature, especially for texture segmentation (Chaudhuri and Sarkar, 1995) and image compression (Fisher, 1995). One of its fundamental definitions is the fractal dimension (FD), a measure of complexity that generalizes the topological dimension concept.

The Multiscale Fractal Dimension (MFD) is an extension of the Minkowski-Bouligand Fractal Dimension, using Euclidean morphological dilations for multiscale representation. Basically, it encodes the value of the fractal dimension as a function of the dilation radius (Costa et al., 2001). An efficient linear-time algorithm for computing the MFD was proposed in (da S. Torres et al., 2004). This method uses the Image Foresting Transform (IFT) (Falcão et al., 2004) – a graph-based approach for the design of operators employing connectivity characteristics.

In (da S. Torres et al., 2004), it is also described how to use MFD as a shape descriptor. Basically, MFD curves are used as feature vectors and are compared using the Euclidean distance. Good results in terms of effectiveness were reported in that article. In

Baccetti Garcia V. and da S. Torres R. (2010).
A SHAPE DESCRIPTOR BASED ON SCALE-INVARIANT MULTISCALE FRACTAL DIMENSION.
In *Proceedings of the International Conference on Computer Vision Theory and Applications*, pages 185-190
DOI: 10.5220/0002831301850190

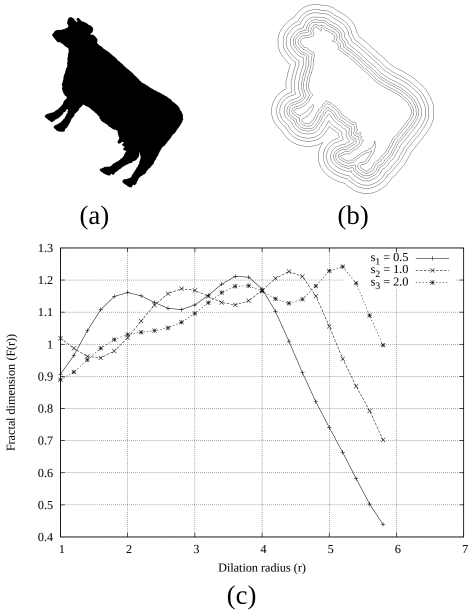


Figure 1: (a) An image extracted from the MPEG-7 data set (Bober, 2001). (b) Dilated contours of (a). (c) The MFD curves of rescaled versions of this image (each of them using a scale factor s_i).

spite of these positive initial results, the MFD shape descriptor has deficiencies regarding scale variance. It can be observed that large contours tend to have fractal curves shifted towards higher dilation radii (see Figure 1). This phenomenon is expected, as smaller contour details become indistinguishable for lower dilation radii, leading to an earlier fall of the curve and a consequent "shift" between feature vectors. In order to achieve scale invariance, it is important that the curves are somehow "aligned".

The descriptor proposed in this paper is based on the Multiscale Fractal Dimension. It introduces a different feature extraction method that guarantees invariance to translation, rotation, and scale transformations. The main changes to the original MFD algorithm are the use of a normalization step prior to the execution of the IFT, a new MFD extraction strategy that guarantees longer fractal dimension curves, and the use of a sliding window for selecting relevant information from the MFD curve. The same distance function, the Euclidean distance, is applied.

Validation was conduced in two different data sets in order to verify the general effectiveness as well as its sensitivity towards the scale transformations. The first database is composed of 99 images (9 classes) being subject to variations in form and also occlusion, articulation, missing parts and segmentation-like errors (Sebastian et al., 2004). The second set was derived from the MPEG-7 database (Bober, 2001), with 700 images divided into 70 classes. Precision $\times$ Recall (Muller et al., 2001) is used to objectively analyze obtained results.

The proposed descriptor is compared to four other approaches available in literature: Beam angle statistics (Arica and Vural, 2003), Fourier Descriptors (Gonzalez et al., 2004), Moment Invariants (Hu, 1962), and Segment Saliences (da S. Torres and Falcão, 2007). Results have shown that the novel descriptor is scale-invariant being comparable to the best descriptors used as baselines in the Kimia data set (Sebastian et al., 2004).

This paper is organized as follows: section 2 presents related work; section 3 describes the proposed scale-invariant shape descriptor; section 4 describes conducted experiments and discusses obtained results; finally, section 5 states the conclusions and discusses future work.

2 RELATED WORK

This section presents the Image Foresting Transform (IFT) (Falcão et al., 2004) and describes its use for obtaining the MFD (da S. Torres et al., 2004).

2.1 Image Foresting Transform

The Image Foresting Transform (IFT) (Falcão et al., 2004) is a discrete approach for the design of image processing operators based on connectivity properties. The main idea of this method is to reduce the common image partition problem to find the *minimum-cost path forest* in a graph.

In this paper, we use the Euclidean Distance Transform (EDT) implemented with the IFT (Falcão et al., 2004; da S. Torres and Falcão, 2007). The advantage of computing the EDT via IFT is that its time-complexity is linear.

2.2 Multiscale Fractal Dimension

This section describes an efficient algorithm (da S. Torres et al., 2004) for computing Multiscale Fractal Dimension using the Euclidean Distance Transform obtained with the Image Foresting Transform (IFT).

There are several definitions for fractal dimension (Mandelbrot, 1982). Among these definitions, the Minkowski-Bouligand Fractal Dimension has been one of the most popular in the image analysis community. It can be evaluated by a few different algorithms (Costa et al., 2001). This fractal dimension is defined as: $F = 2 - \lim_{r \to 0} \frac{\log A(r)}{\log(r)}$, where $A(r)$ is the area of a region dilated by a radius r (see Figure 1(b)). The three-step algorithm, described next, is used to compute the Minkowski-Bouligand fractal dimension:

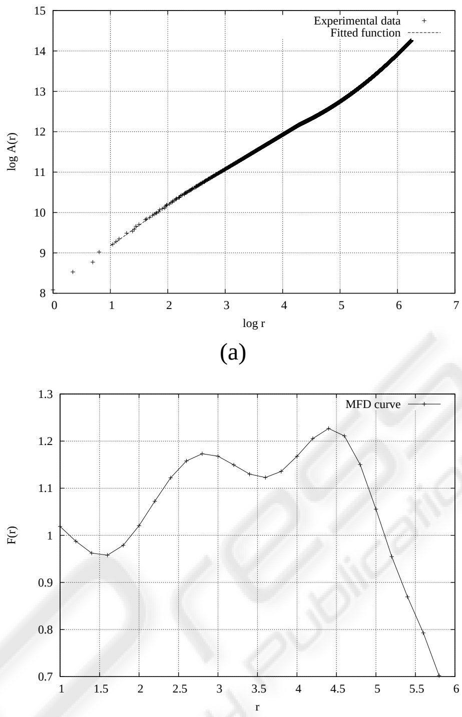
1 - Obtaining the Euclidean Distance Transform. This part consists in the execution of the Image Foresting Transform for obtaining the EDT of the contour. As it will be discussed further ahead, the maximum dilation radius for which the EDT is computed is an important factor for obtaining scale-invariance. For implementation purposes, the maximum dilation radius depends on the size of a large empty frame placed around the input image.

2 - Evaluating Areas of Dilated Contours. By evaluating the cumulative histogram of the cost map (the EDT image), one can determine dilated regions' areas. It is also necessary to compute the $\log \times \log$ of this cumulative histogram.

3 - Regression and Estimation of the Multiscale Fractal Dimension. A common approach for evaluating a single-valued fractal dimension is to linearly fit the $\log A(r) \times \log r$ curve and to consider the fractal dimension F as 2 minus the angular coefficient. Analysing the definition of Minkowski-Bouligand Fractal Dimension, a great similarity with the differentiation can be found. Indeed, both concepts are related to behaviour in an infinitesimal interval. One intuitive generalization is to fit the curve with a function f that is not necessarily a line (in our implementation a polynomial $f_n(r)$ with degree n greater than one). Therefore, instead of a single scalar value, the dilated contours' fractal dimensions can be obtained as a function of their dilation radii: $F(r) = 2 - f_n'(r)$.

In comparison to other methods for evaluation the fractal dimension, this approach avoids the problem of finding a suitable interval for linear regression (as non-linear behaviour is observed for high dilation radii). Comparing to previous methods for extracting the Multiscale Fractal Dimension (Costa et al., 2001), the IFT-based approach does not suffer from undesirable oscillations caused by noise in the estimation of the derivative of a sampled curve.

In Figure 2, there is an example of steps 2 and 3 using the contour shown in Figure 1(a). Figure 2(a) shows the $\log \times \log$ cumulative histogram of the cost map fitted with a polynomial of degree n ($n = 25$). Finally, Figure 2(b) presents the multiscale fractal dimension. The feature vector contains 25 samples of the MFD curve for $r \in [1, 6]$.



(a)

(b)

Figure 2: Using the image shown in Figure 1(a), (a) its $\log(A)(r) \times \log(r)$ values fitted by a function f_n and (b) its Multiscale Fractal Dimension.

3 SCALE-INVARIANT MULTISCALE FRACTAL DIMENSION

The Scale-Invariant Multiscale Fractal Dimension (SIMFD) aims to use the shape description properties of MFD curves while avoiding their sensitivity towards scale change. As explained in the introduction (see Figure 1), larger images have shifted fractal curves.

The proposed method used to avoid scale variation is based on the idea of aligning curves during the feature vector evaluation. The alignment method relies on extracting a fragment of the MFD curve using a sliding window of fixed length. In order to guarantee that this window can extract relevant fragments (those that characterize the complexity of a contour), two strategies are used before the alignment: normalization of the input image before computing the IFT, and the use of a modified MFD extraction method. These two strategies are explained, respectively, in sections 3.1 and 3.2. The use of the sliding window for selecting the relevant fragment of the MFD curve is described in Section 3.3.

3.1 Pre-IFT Scale Normalization

Fractal curves of very small images decrease very quickly, not having enough information to characterize the shape complexity. Such problem can be avoided easily by defining a minimum size for the area of the Minimum Bounding-Box (MBB) around the object whose contour is being described. Images that are below this threshold are rescaled. The threshold value (minimum area) used in our experiments was 512×512. Higher values did not improve the effectiveness of the method significantly.

3.2 Maximum Dilation Radius for MFD

Problems can also happen when images are too large. The difficulty is that fractal curves might fall too late, hampering the definition of the suitable curve fragment that should be used for shape description. In order to solve this problem, we propose a modified MFD extraction method.

In the technique described in Section 2.2, the MFD curve is sampled in a fixed dilation radius interval. The lower bound cannot be changed, as it is directly impacted by the regression stability. The upper bound – the maximum dilation radius – can nevertheless be modified. Our proposal is that this value should be proportional to the square root of the image area. In this way, fractal curves of large images are longer, having enough information about the shape complexity. In our experiments the upper bound value t_{ub} is defined as follow: $t_{ub} = 2 \times \sqrt{A}$, where A is the area of the object's MBB.

3.3 Curve Fragment Selection

The following properties are true for a MFD curve $F(r)$ of a closed contour:

$$\begin{cases} F(r) \in [0,2] & (1) \\ max(F(r)) \geq 1 & (2) \\ \lim_{r \to \infty} F(r) = 0 & (3) \end{cases}$$

where r is the dilation radius.

A sliding window of length W is used to find a radius r_c in which $F(r_c) = F_c$ for a fixed F_c. The feature vector is defined as the N multiscale fractal dimension values sampled in the interval $[r_c - W \times p, r_c + W \times (1-p)]$. The parameter p is used to define the proportion of points inside the window in which dilation radii are smaller than r_c. Figure 3 illustrates how those parameters relate to each other.

Notice that, from Equations 2 and 3, if $F_c \in [1, 0[$ then there exists a r_c in which $F(r_c) = F_c$. Therefore,

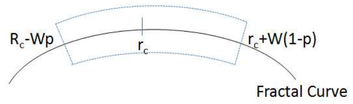
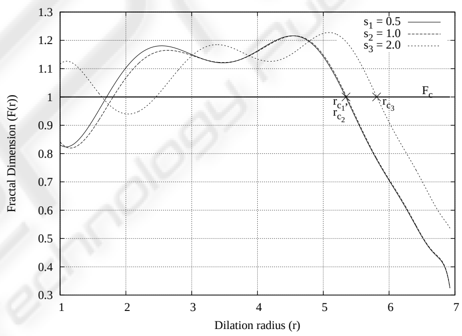


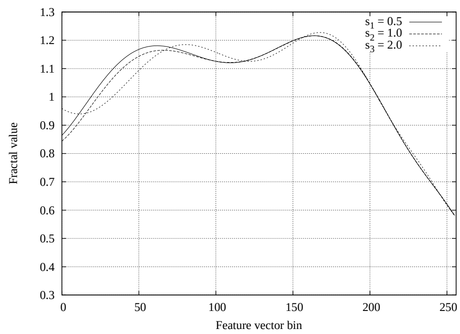
Figure 3: Window parameters.

if the curve is long enough, the radius r_c can be found by the sliding window. Moreover, it is necessary that the sampling lower bound ($r_c - W \times p$) be larger than the minimum dilation radius and that upper bound ($r_c + W \times (1-p)$) be smaller than the maximum dilation radius. Those requirements are fulfilled by using the approaches described in sections 3.1 and 3.2.

In our experiments, $W = 5$, $p = 0.8$, and $F_c = 1.0$. There are 256 samples and the polynomial degree is 25. Examples of feature vectors are shown in Figure 4. It is possible to see the normalization effects by comparing these feature vectors to the MFD values in Figure 1.



(a)



(b)

Figure 4: Results of the SIMFD for three rescaled versions of Figure 1(a) using different scale factors' values of s_i: (a) MFD curves prior to fragment selection (notice the x_{ci} and F_c), (b) SIMFD feature vectors.

4 EXPERIMENTS

In this section, the proposed descriptor (SIMFD) is compared with the earlier definition of MFD (da S. Torres et al., 2004) and other shape descriptors as well. Precision $\times$ Recall curves are used as the effectiveness measure to evaluate performance.

4.1 Shape Data Sets

Finding good databases for shape description can be difficult, as most of available data sets are formed by colour and texture images. Moreover, contour-based shape descriptors restrict even more the choice of data sets, as images must have a single closed contour without internal cavities. The MPEG-7 database is extensively used in literature (Bober, 2001), however it has classes that might not be suitable to many contour-based descriptors (see Figure 5). In our experiments, the following data sets are employed:

Scale invariance tests data set: derived from the Core Experiments Shape 1 Part B data set (Bober, 2001), this database contains 700 images divided into 70 classes. It has been created by randomly choosing one image from each class of the former database and by scaling them up and down by fixed factors.

Kimia-99 data set: this database has 99 images separated into 9 classes which have been subject to form variations as well as occlusion, articulation, missing parts, etc. (Sebastian et al., 2004). This database has been frequently employed for the validation of contour-based shape descriptors (Ling and Jacobs, 2007; Yang et al., 2008).

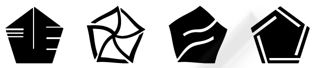


Figure 5: Example of images of a MPEG-7 class that are not suitable for contour-based shape descriptors.

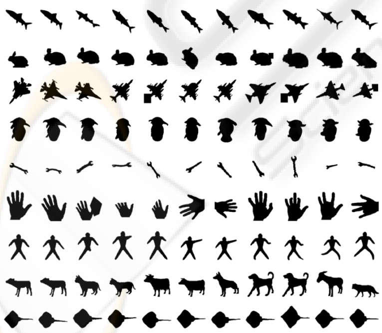
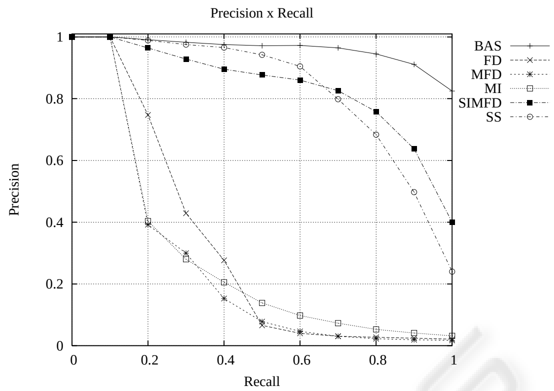


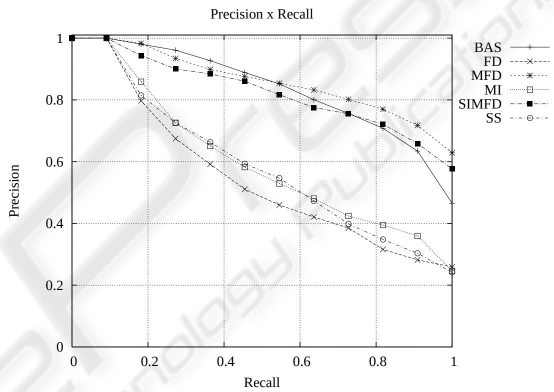
Figure 6: Images of the Kimia-99 data set.

4.2 Descriptors used for Comparison

The new descriptor and the original proposition (da S. Torres et al., 2004) is referred as, respectively, SIMFD and MFD. Besides these two algorithms, the following descriptors are also used: **Beam angle statistics (BAS)** (Arica and Vural, 2003); **Fourier Descriptors (FD)** (Gonzalez et al., 2004); **Moment invariants (MI)** (Hu, 1962); and **Segment saliences (SS)** (da S. Torres and Falcão, 2007).



(a)



(b)

Figure 7: Precision $\times$ Recall graphs for (a) the Scale invariance data set, and for (a) the Kimia-99 shape data set.

4.3 Experimental Results

Considering the two data sets, the Precision $\times$ Recall curves are shown in Figure 7. Regarding the scale invariance tests (Figure 7(a)), it can be observed that the Scale-Invariant Multiscale Fractal Dimension is more effective than the original MFD descriptor. Other descriptors have different sensitivities to scale. BAS is the most invariant descriptor.

For the general effectiveness experiments in the Kimia-99 data set (Figure 7(b)), two different groups of descriptors can be noticed in the Precision $\times$ Recall graph. The effectiveness results of descriptors of each group are almost the same. BAS, MFD, and SIMFD yield the best effectiveness measures. FD, MI, and SS have similar effectiveness performance, being largely outperformed by BAS, MFD, and SIMFD, which have similar effectiveness performance. It is important to note that in this data set there is almost no scale variance (see Figure 6).

5 CONCLUSIONS

This article presented a novel shape description algorithm, the Scale-Invariant Multiscale Fractal Dimension (SIMFD). This descriptor is based on the use of the Fractal Dimension concept – a real number that describes boundary complexity and self-affinity characteristics. The proposed method relies on three steps: a pre-IFT area normalization, the use of a new algorithm for obtaining the multiscale fractal dimension, and the use of a method for extracting the most relevant fragment of the MFD curve.

An experimental validation was conduced, comparing SIMFD to the Multiscale Fractal Dimension and to four other shape descriptors. Experiments results have shown that the new descriptor is at least as effective as the Beam Angle Statistics and the Multiscale Fractal Dimension, outperforming other well-known shape descriptors. Moreover, it has been empirically demonstrated that SIMFD is scale-invariant.

Future work includes extending the proposed descriptor to more complex binary images (several contours, cavities inside the shape, etc.). Extending the description algorithm to grey-scale images is also being studied.

ACKNOWLEDGEMENTS

Authors thanks CNPq, CAPES, and FAPESP for financial support.

REFERENCES

Arica, N. and Vural, F. (2003). BAS: a perceptual shape descriptor based on the beam angle statistics. *Pattern Recognition Letters*, 24(9–10):31–41.

Bober, M. (2001). MPEG–7 visual shape descriptors. *IEEE Transactions on Circuits and Systems for Video Technology*, 11(6):716–719.

Chaudhuri, B. and Sarkar, N. (1995). Texture segmentation using fractal dimension. *PAMI*, 17(1):72–77.

Costa, L., Campos, A., and Manoel, E. (2001). An integrated approach to shape analysis: Results and perspectives. In *International Conference on Quality Control by Artificial Vision*, pages 23–34.

da S. Torres, R. and Falcão, A. (2007). Contour salience descriptors for effective image retrieval and analysis. *Image and Vision Computing*, 25(1). 3–13.

da S. Torres, R., Falcão, A., and da F. Costa, L. (2004). A graph–based approach for multiscale shape analysis. *Pattern Recognition*, 37(6):1163–1174.

Datta, R., Joshi, D., Li, J., and Wang, J. Z. (2008). Image retrieval: Ideas, influences, and trends of the new age. *ACM Computing Surveys*, 40(2):1–60.

Falcão, A., Stolfi, J., and de A. Lotufo, R. (2004). The image foresting transform: Theory, algorithms, and applications. *PAMI*, 26(1):19–29.

Fisher, Y. (1995). *Fractal image compression: theory and applications*. Springer-Verlag, New York.

Gonzalez, R., Woods, R., and Eddins, S. (2004). *Digital image processing using MATLAB*. Prentice Hall Upper Saddle River, NJ.

Hu, M. (1962). Visual pattern recognition by moment invariants. *IRE Trans. on Inf. Theory*, 8(2):179–187.

Ling, H. and Jacobs, D. (2007). Shape classification using the inner-distance. *PAMI*, 29(2):286–299.

Liu, Y., Zhang, D., Lu, G., and Ma, W. (2007). A survey of content-based image retrieval with high-level semantics. *Pattern Recognition*, 40(1):262–282.

Mandelbrot, B. (1982). *The Fractal Geometry of Nature*. W. H. Freeman, San Francisco, CA, USA.

Muller, H., Muller, W., Squire, D., Maillet, S., and Pun, T. (2001). Performance evaluation in content-based image retrieval: Overview and proposals. *Pattern Recognition Letters*, 22(5):593–601.

Sebastian, T. B., Klein, P. N., and Kimia, B. B. (2004). Recognition of shapes by editing their shock graphs. *PAMI*, 26(5):550–571.

Yang, X., Bai, X., Latecki, L. J., and Tu, Z. (2008). Improving shape retrieval by learning graph transduction. In *ECCV*, pages 788–801.

Zhang, D. and Lu, G. (2004). Review of shape representation and description. *Pattern Recognition*, 37(1):1–19.