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Image Pattern Recognition using Near Sets

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Abstract. The problem considered in this paper[1] is how to recognize similar objects based on the detection of patterns in pairs of images. This article introduces a new form of classifier based on approximation spaces in the context of near sets for use in pattern recognition. By way of introducing the basic approach, nonlinear diffusion is used for edge detection and object contour extraction. This form of image transformation makes it possible to compare the contours of objects in pairs of images. Once the contour of an image has been identified, it is then possible to construct approximation spaces based on vectors of probe function measurements associated with selected image features. In this article, the only feature considered is *contour*, which leads to many contour probe functions. The contribution of this article is a new form of classifier, based on approximation spaces, for use in image pattern recognition.

Keywords: Approximation space, near sets, image, feature extraction, nonlinear diffusion, pattern recognition, rough sets.

1 Introduction

The problem considered in this paper is how to recognize similar objects based on the detection of patterns in pairs of images. The proposed solution to this problem utilizes approximation spaces introduced by Zdzisław Pawlak (see, *e.g.*, [4, 5]), later generalized in [8], and further refined in [6]. In this paper, the approach to approximation space-based image pattern recognition is strictly limited to discovering similar objects in images based on object contours. Specifically, a user creates a template image by creating a "sketch." The goal is then to obtain all images within a database that match the template. The results reported in this article are limited to three unknown objects, two that match the template, and one that does not. Nonlinear diffusion is used for image smoothing and object contour extraction. The traditional approach suggested in [3], for recognition of an object in an image $\mathcal{I}$ with a suspected match in an image I_1 is performed by comparing probe function values in

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$$\mathcal{I} \approx (I_1)T \Leftrightarrow |f(\mathcal{I}) - f(I_1)| < \varepsilon, \forall f, \varepsilon \in [0, 1]$$

where $\mathcal{I}$ is approximately the same as I_1 after some transformation T, iff $|f(\mathcal{I}) - f(I_1)| < \varepsilon$ for all f associated with, *e.g.*, the *contour* of an object in an image. In contrast, the approach taken in this article is to match a sketch drawn by a user with an object contained in an image by recording contour probe function values of both objects in a data table and constructing an approximation space. Lower rough coverage values are then used to determine if the template image is a match to the unknown image. The contribution of this article is a new form of approximation space-based classifier for use in image pattern recognition.

This article is organized as follows. An approach to edge detection is briefly presented in Section 2. Sections 3 and 4 briefly present the fundamentals of approximation spaces with respect to near sets and their application to pattern recognition, respectively. Finally, sample results of the proposed approach are presented in Section 5.

2 Edge detection

Sketches inherently represent edges of the objects we are trying to match. Consequently, a natural place to start is with image segmentation, which is the process of partitioning an image into regions that are representative of the objects within the image [2]. This can be accomplished by identifying the edges which are high contrast regions of an image. This article uses nonlinear diffusion image filtering to achieve segmentation (and subsequently perform edge detection). This method is based on actual physical processes such as the diffusion of heat in a metal bar [1, 9, 10]. The process is considered nonlinear because the diffusivity becomes a decreasing function of the magnitude of the gradient, since the gradient will produce a large value in areas of large contrast (edges within the image) [9]. The result is that uniform (low gradient magnitude) areas within the image undergo more diffusion than areas with high contrast (high gradient magnitude). An example of nonlinear diffusion is given in Fig. 1 using the nonlinear diffusion toolbox for Matlab [1].

3 Approximation spaces

This section introduces a view of approximation spaces defined in a slightly modified manner in comparison with the original definition in [8]. Any generalized approximation space (GAS) is a tuple

$$GAS = (U, A, N_r, \nu_B),$$

where U is the universe (elements of U may be, for example, objects, behaviours, or perhaps states), A is a set of probe functions (such that $x \in U$ and $f(x) \in A$), N_r is a neighbourhood family function and ν_B is an overlap function defined by

1.1: Original image

1.2: Segmentation using nonlinear diffusion

1.3: Binary contour using nonlinear diffusion

Fig. 1: Results of nonlinear diffusion on an image

$$\nu_B : \mathcal{P}(U) \times \mathcal{P}(U) \longrightarrow [0, 1], \tag{1}$$

where and $\mathcal{P}(U)$ is the powerset of U [6]. Equation 1 maps a pair of sets to a number in $[0, 1]$ representing the degree of overlap between the sets of objects with features defined by $B \subseteq A$ [8]. For each subset $B \subseteq A$ of probe functions, define the binary relation $\sim_B = \{(x, x') \in U \times U : \forall f \in B, f(x) = f(x')\}$. Since each $\sim_B$, is an equivalence relation (*i.e* the Ind_B indiscernibility relation), for $B \subset A$ and $x \in U$ let $[x]_B$ denote the equivalence class, or *block*, containing x, that is,

$$[x]_B = \{x' \in U : \forall f \in B, f(x') = f(x)\} \subseteq U.$$

If $(x, x') \in \sim_B$ (also written $x \sim_B x'$) then x and x' are said to be B-*indiscernible*. Then define a family of neighborhoods $N_r(A)$, *i.e.*,

$$N_r(A) = \bigcup_{B \subseteq P_r(A)} [x]_B,$$

where $P_r(A) = \{B \subseteq A \mid |B| = r\}$ for any r such that $1 \leq r \leq |A|$. That is, r denotes the number of features used to construct families of neighborhoods. Information about a sample $X \subseteq U$ can be approximated from information contained in B by constructing a $N_r(B)$-lower approximation

$$N_r(B)_* X = \bigcup_{x : [x]_B \subseteq X} [x]_B,$$

and a $N_r(B)$-upper approximation

$$N_r(B)^* X = \bigcup_{x : [x]_B \cap X \neq \emptyset} [x]_B.$$

Then $N_r(B)_*X \subseteq N_r(B)^*X$ and the boundary region $BND_{N_r(B)}(X)$ between upper and lower approximations of a set X is defined to be the complement of $N_r(B)_*X$, *i.e.*

$$BND_{N_r(B)}(X) = N_r(B)^*X \backslash N_r(B)_*X = \{x \in N_r(B)^*X \mid x \notin N_r(B)_*X\}.$$

A family of neighborhoods $N_r(B)$ is near a set X *iff* $|BND_{N_r(B)}(X)| \geq 0$. This means every rough set is a near set but not every near set is a rough set. Lastly, use the notation $B_j(x)$ to denote a subset of $N_r(B)$, where $j \in B$. Put

$$\nu_j(B_j(x), N_r(B)_*X) = \begin{cases} \frac{|B_j(x) \cap N_r(B)_*X|}{|N_r(B)_*X|}, if N_r(B)_*X \neq \emptyset, \\ 1, \qquad\qquad\qquad\quad if N_r(B)_*X = \emptyset, \end{cases} \tag{2}$$

where ν_j is a specialized form of rough coverage (see, *e.g.*, [7]).

4 Approximation spaces and pattern recognition

It is now possible to formulate a basis for object recognition, which parallels the traditional formulation of pattern recognition. Let $X = D$ represent a decision class containing all elements of U obtained from the template image using probe functions from B. D represents a standard for classifying images. Observe that a non-zero rough coverage value ν_j means that $B_j(x)$ contains elements that are members of the decision class D. Further, a larger number of non-zero coverage values implies that a significant number of blocks contain elements that are part of the decision class (the template image). Consequently, the ratio of non-zero coverage values to total coverage values can be used as a new form of image classifier. Put,

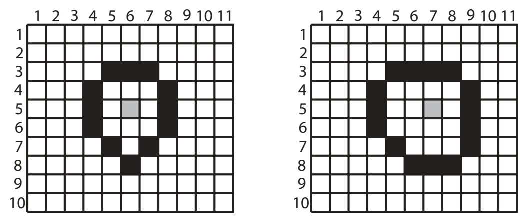
$$C_\nu(GAS) = \frac{|\{\nu_j : \forall B_j(x) \in N_r(B), \nu_j > 0\}|}{|\{\nu_j : \forall B_j(x) \in N_r(B)\}|},$$

where $C_\nu(GAS)$ is the ratio of non-zero coverage values to total coverage values obtained from a specific GAS (for convenience we simply write C_ν). Then recognition of objects that are approximately the same is defined by comparing non-zero coverage ratios using

$$\mathcal{O} \approx (\mathcal{O}_{id})T \Leftrightarrow C_\nu > \varepsilon,$$

where $\varepsilon \in [0, 1]$. That is to say, the object $\mathcal{O}$ is approximately the same as $\mathcal{O}_{id}$ after some transformation T whenever C_ν is greater than some ε.

By way of an illustration of the utility of approximation spaces, a near set approach to pattern recognition is briefly considered here. Recall that the goal of this process is to match a template with an unknown image. Let us define a decision system as a data table (U, A) such that A contains a distinguished probe function d representing a decision. Thus the set $D \subseteq U$ consists of all the elements for which $d(x) = 1$. The first step in creating a decision system is to create the data table. Such tables will then be used to set up approximation spaces to determine the degree that an object in an image resembles the template. The approach used in this article is to create a data table from two images where all elements associated with the template make up the decision class D. Two such tables are given in Tables 1 and 2 created from the images shown in Fig. 2. Table 1 represents the ideal case in which the template in Fig. 2.1 is compared with itself. Similarly, Table 2 contains data obtained from comparing the template in Fig. 2.1 with the unknown image given in Fig. 2.2.



2.1: Template image   2.2: Unknown image

Fig. 2: Contour comparison

Table 1: Decision system for Fig. 2.1

x_i	Probe functions $f_0 \cdots f_{10}$											d
$\mathbf{x_0}$	0	0	0	0	0	0	0	0	0	0	0	1
$\mathbf{x_1}$	0	0	0	0	0	0	0	0	0	0	0	1
$\mathbf{x_2}$	0	0	0	0	3	2	3	0	0	0	0	1
$\mathbf{x_3}$	0	0	0	3	0	0	0	3	0	0	0	1
$\mathbf{x_4}$	0	0	0	2	0	0	0	2	0	0	0	1
$\mathbf{x_5}$	0	0	0	3	0	0	0	3	0	0	0	1
$\mathbf{x_6}$	0	0	0	0	3	0	3	0	0	0	0	1
$\mathbf{x_7}$	0	0	0	0	0	3	0	0	0	0	0	1
$\mathbf{x_8}$	0	0	0	0	0	0	0	0	0	0	0	1
$\mathbf{x_9}$	0	0	0	0	0	0	0	0	0	0	0	1
x_{10}	0	0	0	0	0	0	0	0	0	0	0	0
x_{11}	0	0	0	0	0	0	0	0	0	0	0	0
x_{12}	0	0	0	0	3	2	3	0	0	0	0	0
x_{13}	0	0	0	3	0	0	0	3	0	0	0	0
x_{14}	0	0	0	2	0	0	0	2	0	0	0	0
x_{15}	0	0	0	3	0	0	0	3	0	0	0	0
x_{16}	0	0	0	0	3	0	3	0	0	0	0	0
x_{17}	0	0	0	0	0	3	0	0	0	0	0	0
x_{18}	0	0	0	0	0	0	0	0	0	0	0	0
x_{19}	0	0	0	0	0	0	0	0	0	0	0	0

Table 2: Dec. sys. for Figs. 2.1 and 2.2

x_i	Probe functions $f_0 \cdots f_{10}$											d
$\mathbf{x_0}$	0	0	0	0	0	0	0	0	0	0	0	1
$\mathbf{x_1}$	0	0	0	0	0	0	0	0	0	0	0	1
$\mathbf{x_2}$	0	0	0	0	3	2	3	0	0	0	0	1
$\mathbf{x_3}$	0	0	0	3	0	0	0	3	0	0	0	1
$\mathbf{x_4}$	0	0	0	2	0	0	0	2	0	0	0	1
$\mathbf{x_5}$	0	0	0	3	0	0	0	3	0	0	0	1
$\mathbf{x_6}$	0	0	0	0	3	0	3	0	0	0	0	1
$\mathbf{x_7}$	0	0	0	0	0	3	0	0	0	0	0	1
$\mathbf{x_8}$	0	0	0	0	0	0	0	0	0	0	0	1
$\mathbf{x_9}$	0	0	0	0	0	0	0	0	0	0	0	1
x_{10}	0	0	0	0	0	0	0	0	0	0	0	0
x_{11}	0	0	0	0	0	0	0	0	0	0	0	0
x_{12}	0	0	0	0	4	3	2	3	0	0	0	0
x_{13}	0	0	0	4	0	0	0	0	3	0	0	0
x_{14}	0	0	0	3	0	0	0	0	2	0	0	0
x_{15}	0	0	0	4	0	0	0	0	3	0	0	0
x_{16}	0	0	0	0	4	0	0	0	4	0	0	0
x_{17}	0	0	0	0	0	4	3	4	0	0	0	0
x_{18}	0	0	0	0	0	0	0	0	0	0	0	0
x_{19}	0	0	0	0	0	0	0	0	0	0	0	0

Moreover, to populate the tables, the coordinates of the centroid of each image are calculated to find the geometric centre of the image (the grey pixels in the centres of the contours). Next, the distances from the centroid are calculated using the taxicab metric for each point on the contour of each image. Note, distances are only reported for points on the contour. Lastly, what follows is an example showing how to obtain $C_\nu = 1$ for Table 1. Similar calculations produce a value of $C_\nu = 0.592593$ for Table 2. Observe that Table 2 produces a lower value of C_ν since Fig. 2.1 and Fig. 2.2 are not identical.

Decision class: $D = \{x_0, x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9\}$

$B_j(x)$: $\{\nu_j\}$
$B_{f_0}(x_0) = \{x_0, x_1, x_2,$
$x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}\}$: $\{1.0000\}$
$B_{f_1}(x_0) = \{x_0, x_1, x_2,$
$x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}\}$: $\{1.0000\}$
$B_{f_2}(x_0) = \{x_0, x_1, x_2,$
$x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}\}$: $\{1.0000\}$
$B_{f_3}(x_0) = \{x_0, x_1, x_2, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{16}, x_{17}, x_{18}, x_{19}\}$: $\{1.0000\}$
$B_{f_3}(x_3) = \{x_3, x_5, x_{13}, x_{15}\}$: $\{1.0000\}$
$B_{f_3}(x_4) = \{x_4, x_{14}\}$: $\{1.0000\}$
$B_{f_4}(x_0) =$
$\{x_0, x_1, x_3, x_4, x_5, x_7, x_8, x_9, x_{10}, x_{11}, x_{13}, x_{14}, x_{15}, x_{17}, x_{18}, x_{19}\}$: $\{1.0000\}$
$B_{f_4}(x_2) = \{x_2, x_6, x_{12}, x_{16}\}$: $\{1.0000\}$
$B_{f_5}(x_0) =$
$\{x_0, x_1, x_3, x_4, x_5, x_6, x_8, x_9, x_{10}, x_{11}, x_{13}, x_{14}, x_{15}, x_{16}, x_{18}, x_{19}\}$: $\{1.0000\}$
$B_{f_5}(x_2) = \{x_2, x_{12}\}$: $\{1.0000\}$
$B_{f_5}(x_7) = \{x_7, x_{17}\}$: $\{1.0000\}$
$B_{f_6}(x_0) =$
$\{x_0, x_1, x_3, x_4, x_5, x_7, x_8, x_9, x_{10}, x_{11}, x_{13}, x_{14}, x_{15}, x_{17}, x_{18}, x_{19}\}$: $\{1.0000\}$
$B_{f_6}(x_2) = \{x_2, x_6, x_{12}, x_{16}\}$: $\{1.0000\}$
$B_{f_7}(x_0) = \{x_0, x_1, x_2, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{16}, x_{17}, x_{18}, x_{19}\}$: $\{1.0000\}$
$B_{f_7}(x_3) = \{x_3, x_5, x_{13}, x_{15}\}$: $\{1.0000\}$
$B_{f_7}(x_4) = \{x_4, x_{14}\}$: $\{1.0000\}$
$B_{f_8}(x_0) = \{x_0, x_1, x_2,$
$x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}\}$: $\{1.0000\}$
$B_{f_9}(x_0) = \{x_0, x_1, x_2,$
$x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}\}$: $\{1.0000\}$
$B_{f_{10}}(x_0) = \{x_0, x_1, x_2,$
$x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}\}$: $\{1.0000\}$

$N_r(B)_* X = \{\emptyset\}$
$C_\nu = 1$

5 Results

Again by way of illustration of the approach to recognizing similar objects in images, template images of tea cups (see Fig. 3) were compared to unknown sample image contours (see Fig. 4) obtained by nonlinear diffusion. The goal was to obtain a higher value of C_ν when comparing a sketch of a tea cup with that of a contour obtained from an image of a tea cup. As shown in Table 3, the template image in both cases produces a higher ratio of non-zero lower coverage vales when compared to the contour of a tea cup than that of the fire hydrant.

3.1: Sketch of first tea cup

3.2: Sketch of second tea cup

Fig. 3: Sample sketches (template images)

4.1: First tea cup

4.2: Second tea cup

4.3: Fire hydrant

Fig. 4: Sample image contours

These results are promising, since they show that a lower approximation space in the context of near sets can be used for pattern recognition. However, there is still much to be investigated. For instance, observing the effects of translation and rotation on the sample images. This method should be translation and rotation independent (within some small ϵ). This is due to the fact that this method uses centroid distances that should not change on rotation or translation of the image as long as the entire object is still within an image.

Other problems should be investigated as well. For example, a comparison of other edge detection techniques and the nonlinear diffusion process is required. This method was selected because it had already been implemented. However, it may not be best suited to the task at hand. Also, other edge detection methods may be more attractive in terms of timing. Currently, the proposed method takes several minutes to obtain the gradient. This is fine when comparing two images, but is unrealistic when searching through an archive containing thousands of them. Similarly, other forms of feature extraction should be explored as well. At present, only one feature, namely, *contour* has been considered. Contour probe function measurements constituting the top five distances from the centroid are used. It may be that there are better features or a combination of multiple features that can be used to provide better results. Finally, both ratios were higher for the tea cup images than the fire hydrant, however, there was a large difference between the results obtained for both tea cups. Consequently, thresholding techniques (such as neural networks) need to also be investigated to determine when it is sufficient to say a sample image being considered “matches” the sketch drawn by a user.

Table 3: Sample Results

Decision Systems	Lower coverage ratios
Template image Fig. 3.1 vs. tea cup contour Fig. 4.1	0.521186
Template image Fig. 3.1 vs. fire hydrant contour Fig. 4.3	0.437100
Template image Fig. 3.2 vs. tea cup contour Fig. 4.2	0.515041
Template image Fig. 3.2 vs. fire hydrant contour Fig. 4.3	0.413616

6 Conclusion

This article introduces an approximation space-based classifier for use in image pattern recognition. Initial results are promising inasmuch as templates (obtained from sketches) of target objects (*e.g.*, tea cups) produce higher non-zero coverage ratios when compared to objects in test images and low coverage ratios when compared to other objects (*e.g.*, fire hydrants). However, further instigation is required before definite conclusions can be made about the proposed approach to image.

References

1. F. D’Almeida. Nonlinear diffusion toolbox, 2003.
2. R.C. Gonzalez and R.E. Woods. *Digital Image Processing*. Prentice-Hall, Toronto, 2nd edition, 2002.
3. M. Pavel. *Fundamentals of Pattern Recognition*. Marcel Dekker, Inc., NY, 1993.
4. Z. Pawlak. Classification of objects by means of attributes. *Polish Academy of Sciences, Technical Report PAS 429*, 1981.
5. Z. Pawlak and A. Skowron. Rudiments of rough sets. *Information Sciences*, 177:3–27, 2006.
6. J.F. Peters. Near sets. special theory about nearness of objects. *Fundamenta Informaticae*, 76:1–27, 2007.
7. J.F. Peters and C. Henry. Reinforcement learning with approximations spaces. *Fundamenta Informaticae*, 71(2-3):323–349, 2006.
8. A. Skowron and J. Stepaniuk. Tolerance approximation spaces. *Fundamenta Informaticae*, 27(2-3):245–253, 1996.
9. J. Weickert. *Anisotropic Diffusion in Image Processing*. Ph.d. dissertation, University of Kaiserslautern, 1996.
10. J. Weickert. Applications of nonlinear diffusion in image processing and computer vision. *Acta Mathematica Universitatis Comenianae*, 70(1):33–50, 2001.