Tomasz JAWORSKI, Jacek KUCHARSKI

Lodz University of Technology, Institute of Applied Computer Science

An algorithm for finding visual markers in an infrared camera images based on Fuzzy Spatial Relations

Abstract. *The following paper presents results of developed algorithm that allows finding a set of heated markers visible in previously registered IR image with a thermal camera. Developed tool is found to be helpful in tasks of locating geometry of cold steel cylinder, hardly distinguishable from its background. The approach is based on matching a scene model with fuzzy description of objects of interests. Authors utilize geometry features such as shape, orientation, distance and spatial relations, which are assessed on a basis of fuzzy set theory.*

Streszczenie. *Prezentowany artykuł przedstawia wyniki prac nad algorytmem automatycznego wykrywania znaczników cieplnych w obrazach uzyskiwanych za pomocą kamery termowizyjnej. Opisywana metoda wykorzystuje wnioskowanie rozmyte oparte na rozmytej ocenie kształtu, położenia oraz wzajemnych relacji przestrzenno-kierunkowych obiektów obserwowanych przez kamerę termowizyjną.* ***(Lokalizacja obiektu zimnego stalowego walca na obrazach z kamery termowizyjnej z użyciem rozmytej oceny relacji przestrzennych znaczników cieplnych)****.*

Keywords: fuzzy logic, fuzzy pattern matching, image processing, thermovision.
Słowa kluczowe: logika rozmyta, rozmyte dopasowywanie wzorów, przetwarzanie obrazów, termowizja.

Introduction

The following article presents an algorithm designed to identify and locate heated markers in infrared images. The main idea behind the conducted research was to precisely locate cold steel cylinder (as in figure 3a) which temperature is same as the surrounding environment's. Hence majority of its edges is invisible. To solve this problem, authors have employed a set of hot markers (heated by DC current flow) and fuzzy assessment methods which seems to be natural due to uncertainty implicitly bound to terms like "object A is a rectangle" or mutual relations "object A is to le left of object B". In other words presented algorithm assess spatial relations between discovered objects in an input image in order to detect a set of visual markers on a rotating steel cylinder previously discussed by the authors in [1-3]. Calculated fuzzy features are then processed by a fuzzy inference module, which tries to find a set of objects in proper relations against each other. For directional relations authors have used experience gained in [4].

Upon many measurement campaigns carried out by the authors with a thermal imaging camera, the authors have faced a set of problems with proper camera calibration and camera placement. The most common issue was to set correctly the yaw/pitch/roll angles of the camera on a stand in order to obtain a video stream that would be easy to process by the later algorithms (that mean horizontally located cylinder at screen center). Such a task is simple when the object is hot and clearly visible in the infrared. However the authors were often in need of registering the whole heat exchange process, starting from a cold object, mostly indistinguishable from its background. For this purpose a set of boundary markers was placed on the monitored object and an algorithm to indentify them was developed.

The purpose of the mentioned markers is to properly calibrate the infrared camera position in order to register whole heating process and to recalibrate the camera in case when it was moved or displaced during an experiment.

The algorithm overview

A sample input image with mentioned cylinder and a set of hot markers is shown in figure 3 and 4. There are three markers visible: two vertical along the diameter and one horizontal, under the object. All of them are made of a resistance wire and are about the same length (width of the cylinder is about 124cm and its diameter is 40cm). When a need for calibration occurs, they are powered up by a power supply at 24V and 1A DC current.

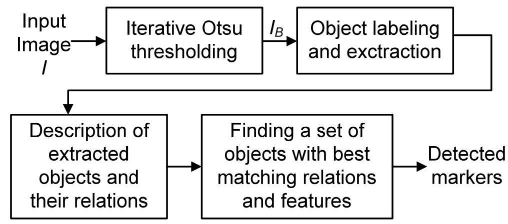

Fig.1. Marker identification algorithm divided into subsequent steps

Due to a total amount of power dispatched by the markers (~75W) the total time of calibration is crucial to avoid any temperature rise on the object's surface. The camera is able to measure up to 50FPS, hence one second of calibration process is sufficient. Hence, a set of 50 frames, obtained from a steady object, is then averaged to attenuate the thermal noise and arrive at the final input image used in the described calibration algorithm shortly presented in figure 1.

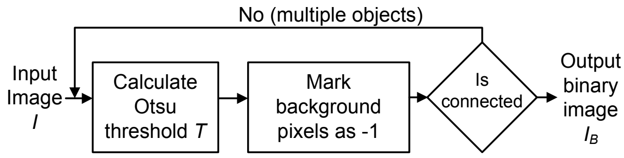

Fig.2. Iterative version of the Otsu algorithm

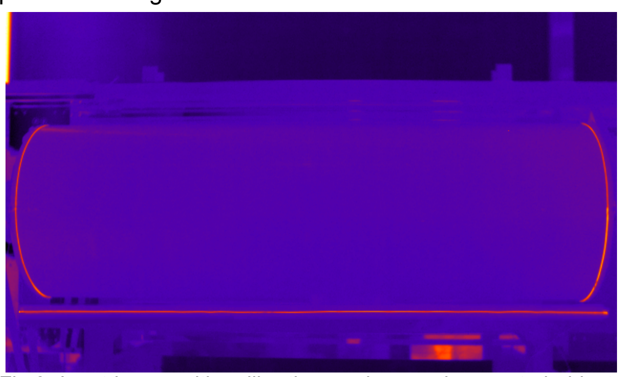

Fig.3. Input image with calibration markers and unwanted objects visible as hotter areas

The obtained input image, depicted in figure 3 is initially processed by the Otsu algorithm [5] in order to extract hot areas, clearly visible over the background. It is executed iteratively (as shown in figure 2) in order to obtain connected background area.

The Otsu algorithm calculates an optimal threshold value T based on the assumption that the input image contains only two classes of pixels – background and foreground, and tries to minimize the intra-class variance. After the Otsu algorithm is executed, background pixels (with values less then T) are removed from further thresholding by simply replacing their values with -1 so that the Otsu histogram calculation routine will ignore them. In the final decision block the set of removed background pixels (marked with -1) is checked for connectedness [6]. If all pixels belong to one 8-connected object, the algorithm finishes. At this point an image I_B is obtained is presented in figure 4. Afterwards a set of 8-connected objects is extracted and labeled. Three of them (labeled 3, 4, 10) are desired markers and the rest is unwanted hot areas from e.g. central heating pipes or human heat reflected by glossy components in the room.

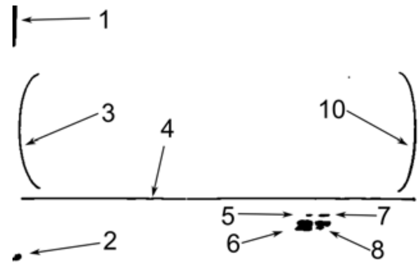

Fig.4. A 8-connected input image with calibration markers and unwanted objects visible as resulting objects for further processing

Features for describing object and relations

In the next step, every extracted object is described. A set of features and relations between each of them is calculated. The following text describes in detail each feature of both object and relation along with their fuzzy assessment.

Distance between two crisp objects [7] is calculated with the following equation:

$$d(R,A) = \inf_{\substack{p \in R \\ q \in A}} d(p,q) \tag{1}$$

where: R, A – Objects (set of points) extracted from I_B, from this point the objects R and A, when in a relation, can be read as **R**eference and **A**rgument, $d(p,q)$ – Euclidean distance between two points p and q.

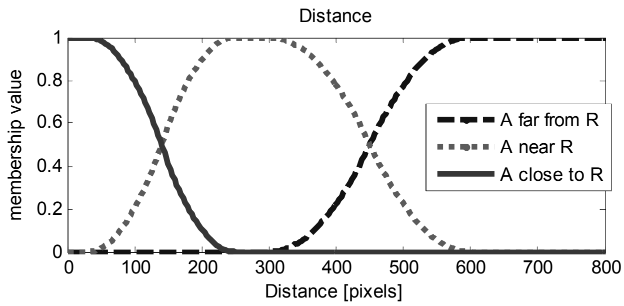

Fig.5. Fuzzy labels for assessing distance between two objects

Equation (1) can be interpreted as shortest distance between any of two points belonging to objects R and A. Obtained value of distance is fuzzified, as shown in figure 5 in order to obtain degrees of truth of expressions "A is far from R" and "A is close R" included in fuzzy variable *Distance*.

Initially the authors have considered using histogram of distances [8] however there was a problem encountered with distance relation between object 3/10 and 4. From their point of view the object 4 (horizontal line) is simultaneously close, near and far. This issue justifies the use of equation (1) and further research is required in order to work out a method for dealing with relation *near/far* in such situations which can be considered both ambiguous and imprecise. Authors believe that this intrinsically gray information can be dealt on a fuzzy set theory basis.

Orientation of an object R is recognized by discovering its major with help of Principal Component Analysis (PCA)

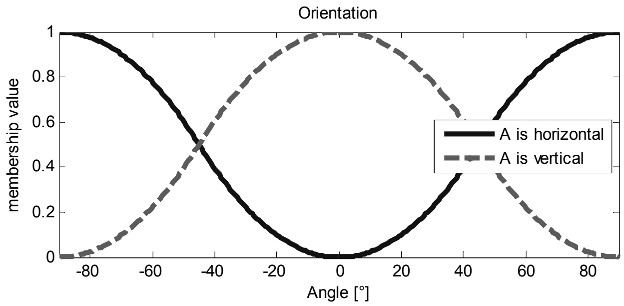

Fig.6. Fuzzy labels for assessing orientation of an object

method [9]. Its functionality of maximizing variance of the first coordinate via rotating given set of points allows the object to be reoriented vertically and to obtain the rotation angle α. For this, one has to calculate eigenvectors matrix $\mathbf{V}$ and diagonal eigenvalues matrix $\mathbf{D}$ of $\mathbf{C}$ through an equation in form $\mathbf{V}^{-1}\mathbf{C}\mathbf{V} = \mathbf{D}$. While $\mathbf{V} \in \Re^{2\times2}$, scalar $\mathbf{V}_{1,2}$ can be used as a rotation angle α of object R with relation to vertical axis. Therefore, equation (2) was used to obtain the angle.

$$\alpha = \operatorname{asin}(\mathbf{V}_{1,2})\frac{180}{\pi} \tag{2}$$

Finally, knowing that object R has to be rotated by angle $-\alpha$ in order to become vertically oriented, one can fuzzify the angle $-\alpha$ to obtain fuzzy variable ***Orientation***. This can be done by a set of fuzzy labels depicted in figure 6.

Shape of the object can be calculated after the PCA analysis, when one knows the object is oriented vertically. In this case equations (3a) and (3b) can be considered as an object's squareness measures.

$$S(R) = \frac{\min\left(\max_{p\in R} x_p - \min_{p\in R} x_p, \max_{p\in R} y_p - \min_{p\in R} y_p\right)}{\max\left(\max_{p\in R} x_p - \min_{p\in R} x_p, \max_{p\in R} y_p - \min_{p\in R} y_p\right)} \tag{3a}$$

$$S(R) = \frac{\min\left(\operatorname{stddev}_{p\in R} p_x, \operatorname{stddev}_{p\in R} p_y\right)}{\max\left(\operatorname{stddev}_{p\in R} p_x, \operatorname{stddev}_{p\in R} p_y\right)} \tag{3b}$$

where: $x(p)$, $y(p)$ – X and Y coordinate of a point p.

Table 1. Results for squareness measure (3a and 3b)

Eq.	Objects									
	1	2	3	4	5	6	7	8	9	10
3a	0.087	0.649	0.191	0.008	0.634	0.328	0.587	0.239	1.000	0.157
3b	0.085	0.629	0.163	0.006	0.677	0.364	0.549	0.250	1.000	0.126

In general the PCA method is used here to find the primary axis of the object. When angle α is known, object can be rotated to align it vertically or horizontally and finally squareness can be calculated. Equation (3a) is based on most outer points of the objects (the outline), both in horizontal as in vertical direction. Since objects have to be 8-connected, this approach is free of outlying points problem. However, this approach enables to use objects with “tails” of diagonally connected pixels which may affect final outcome. To overcome this, the authors propose to use equation (3b) which utilizes standard deviation instead of most distant points as in the former case.

Value obtained by equation (3a) and (3b) can be used to distinguish between three shapes:

- square with S close to 1 (or equal)
- line with S close to 0 (but never equal)
- rectangle with S $\in$ (0,1)

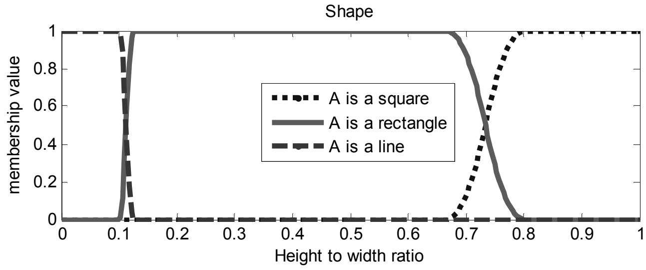

Fig.7. Fuzzy variable for shape description

Due to the vague boundary between square, rectangle and line, the shape feature can be considered as the most appropriate to be fuzzified and used as such. For this purpose the authors have proposed forms of three fuzzy labels appropriate for shape assessment in order to arrive at fuzzy variable ***Shape***, as depicted in figure 7.

A ***Direction*** relation of two objects: a reference object R and an argument object A was obtained by Histogram of Angles method, called also Compatibility Method, which was introduced by Miyajima and Ralescu [10, 11] and analyzed further in [12]. Its main idea relies on the similarity comparison between fuzzy labels describing a relation, which membership function is given by one of the plots in figure 8 or 9b and a histogram (4) interpreted as an unlabeled fuzzy set. More detailed information about directional spatial relation is available from the authors in [4].

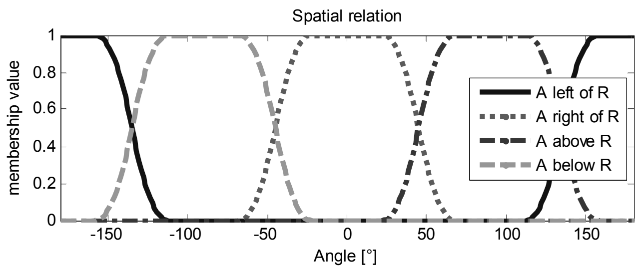

Fig.8. Fuzzy variable for describing directional spatial relation

Let’s assume, that there exists two objects, R and A, with points respectively r_i and a_j, where $i = 1..n$ and $j= 1..m$. For each pair (r_i, a_j) an angle has to be calculated, with formula $\theta_{ij} = \angle(r_i, a_j)$, where the angle is measured between line r_ia_j and horizontal line (the abscissa) passing through the r_i, as depicted in figure 9a.

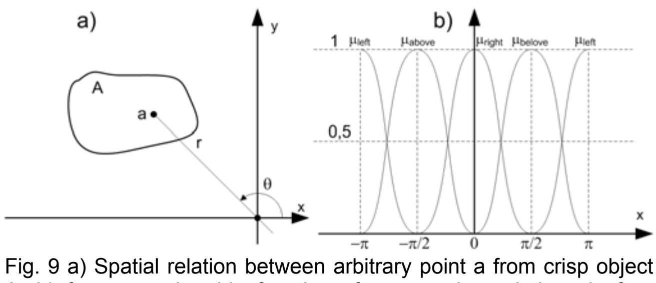

Fig. 9 a) Spatial relation between arbitrary point a from crisp object A; b) fuzzy membership functions for assessing relations in four cardinal directions.

A multiset $\Theta=\{\theta_{ij}\}$ is obtained as a result. Let $f_\Theta(\theta)$ be the count of angle θ in the multiset Θ, $f_\Theta(\theta) = |\{(r_i, a_j):\angle(r_i, a_j) = \theta\}|$. With such input, one can obtain the Histogram of Angles $H_\Theta(R, A) = \{(\theta, f_\Theta(\theta))\}$. In its normalized form it is given by equation (4).

$$H_\Theta(R,A) = \left\{\left(\theta, \frac{f_\Theta(\theta)}{\max\limits_{\varphi} f_\Theta(\varphi)}\right)\right\} \quad (4)$$

Now expression $H_\Theta(R, A)$ can be considered as an unlabeled fuzzy set, which can be interpreted as “*the spatial relation between R and A*”. At this point one can use a compatibility [13] measure of two fuzzy sets or Zadeh Extension Principle denoted by (5).

$$\mu_{CP(H_\Theta,REL)}(v) = \begin{cases} 0 & \{s : v = \mu_{REL}(s)\} = \varnothing \\ \sup\limits_{\{s:v=\mu_{REL}(s)\}} \mu_{H_\Theta}(s) & \{s : v = \mu_{REL}(s)\} \neq \varnothing \end{cases}; \quad v \in [0;1] \quad (5)$$

In equation (5) REL denotes fuzzy set of assessed relation type, like depicted in Figure 8 or 9b. $CP(H_\Theta, REL)$ is a fuzzy set for compatibility evaluation between H_Θ and REL. The final assessment value, *a degree to which tested relation holds*, can be calculated from function $\mu_{CP(H\Theta,\ REL)(v)}$ with use of Center of Gravity [14] method of defuzzification, given by equation (6).

$$compatibility = \frac{\int_0^1 v\mu_{CP(H_\Theta,REL)}(v)dv}{\int_0^1 \mu_{CP(H_\Theta,REL)}(v)dv} = \frac{\sum_{v=0}^{1} v\mu_{CP(H_\Theta,REL)}(v)}{\sum_{v=0}^{1} \mu_{CP(H_\Theta,REL)}(v)} \quad (6)$$

Scene description and fuzzy inferring

As the previous step is done, one has a set of features describing every object and relation between every pair of objects. With this data available, a fuzzy inference about the content of the input image can be carried out. In order to complete this task, there is a need to describe desired relations in the scene by a set of fuzzy expressions. As it was mentioned in the Introduction, the goal of this paper is to detect and distinguish a set of markers on the thermal image. The authors propose the following description for the term *a valid set of markers*:

A **set of markers**, composed of three objects: A1, A2 and B is **valid**

if and only if

A1 is a *rectangle* and **A2** is a *rectangle* and **B** is a *line* and
A1 is *oriented vertically* and **A2** is *oriented vertically* and **B** is *oriented horizontally* and
A1 is *on the left* of **A2** and **A2** is *on the right* of **A1** *or* **A1** is *on the right* of **A2** and **A2** is *on the left* of **A1** and
A1 is *close to* **B** and **A1** is *not near* **B** and **A2** is *close to* **B** and **A2** is *not near* **B** and **A1** is *far* from **A2**

then

selected object triple (X,Y,Z): X as A1, Y as A2 and Z as B is a valid set of markers

The above set of rules was used to obtain membership of truth for the “*valid set of markers*” term and was applied to every triple of objects, assuming X, Y and Z are unique in selected triple. Fuzzy operators: product (*and*) and sum (*or*) were defined by respectively *min* and *max*. Number of triples produced by the algorithm can be obtained from equation (7):

$$N = o(o-1)(o-2) \tag{7}$$

where: o – number of objects found and labeled in an input image, N – number of triples used for fuzzy inference

Results

Presented algorithm was applied to the input image, depicted in figure 3. There were 10 objects found in the image, yielding 720 triples of unique objects. The following table 2 presents obtained results of the algorithm. Only results with μ_{valid} greater than zero were shown.

Table 2. Obtained results for given input image and 10 objects

With alternative					Without alternative				
B	A1	A2	μ_{valid} Eq. 3a	μ_{valid} Eq. 3b	B	A1	A2	μ_{valid} Eq. 3a	μ_{valid} Eq. 3b
4	2	5	0.0092	0.0092	4	2	5	0.0092	0.0092
4	2	6	0.0020	0.0020	4	2	6	0.0020	0.0020
4	2	7	0.0191	0.0191	4	2	7	0.0191	0.0191
4	2	8	0.0016	0.0016	4	2	8	0.0016	0.0016
4	2	10	0.2008	0.2008	4	2	10	0.2008	0.2008
4	3	5	0.0092	0.0092	4	3	5	0.0092	0.0092
4	3	6	0.0020	0.0020	4	3	6	0.0020	0.0020
4	3	7	0.0191	0.0191	4	3	7	0.0191	0.0191
4	3	8	0.0016	0.0016	4	3	8	0.0016	0.0016
4	**3**	**10**	**0.9626**	**0.9626**	**4**	**3**	**10**	**0.9626**	**0.9626**
4	5	2	0.0092	0.0092					
4	5	3	0.0092	0.0092					
4	6	2	0.0020	0.0020					
4	6	3	0.0020	0.0020					
4	7	2	0.0191	0.0191					
4	7	3	0.0191	0.0191					
4	8	2	0.0016	0.0016					
4	8	3	0.0016	0.0016					
4	10	2	0.2008	0.2008					
4	**10**	**3**	**0.9626**	**0.9626**					

Two rows were marked gray: objects 4,3,10 and objects 4,10,3 based on the highest level of membership value μ_{valid}. When comparing them with objects shown in figure 4, one can easily see that only these two rows contain valid identifiers of objects, which can be considered as valid markers. To understand the existence of two rows, the authors suggest to take a closer look at the third expressions group of the fuzzy rule base. Proposed expression deliberately allows the alternative due to the experimental reasons. Removing of the second alternative results in only one triple with highest membership value. Such situation is show in table 2 under "Without alternative". It is also worth to mention, that in case of this experiment, values in table 1 with squarenesses of separated objects differs in values, however in overall calculations the differences do not influence the final outcome (results in table 2 are equal for both equations). The reasons behind this are the forms of Shape fuzzy labels (in figure 7). They were selected by the authors as the answer to question "*When a square becomes a rectangle and a rectangle becomes a line?*"

Presented algorithm was tested on various input images of the same scene but from slightly different point of view. On each image, however, all markers are clearly visible. The results yielded for each of them were satisfactory and from this point the authors are developing next stages of the auto-calibration algorithm that would speed up and ease setting up measurement equipment for each experiment with thermal camera.

Acknowledgments

This research was partially supported by a research project N N519 579838 from Polish National Science Centre.

REFERENCES

[1] Kucharski J., Zgraja J., Urbanek J. Frączyk A., 3D modeling of electromagnetic-thermal fenomena in induction heated rotating steel cylinder, *Automatyka - Zeszyty Naukowe AGH* 15 (2011), nr 3, 403–411

[2] Jaworski T., Kucharski J., Preprocessing and clusterization of thermal images of induction heated steel cylinder, *Automatyka - Zeszyty Naukowe AGH*, 15 (2011), nr 3, 143–160

[3] Urbanek P., Kucharski J., Modeling of dynamic properties of induction heated rotating steel cylinder, in *Proceedings of the 13th IEEE/IFAC International Conference on Methods and Models in Automation and Robotics, IEEE/IFAC International Conference on Methods and Models in Automation and Robotics* (2007)

[4] Jaworski T., Kucharski J., The use of fuzzy logic for description of spatial relations between objects, *Automatyka - Zeszyty Naukowe AGH*, 14 (2010), nr 3/1, 563–580

[5] Otsu N., Threshold selection method from gray-level histograms, *IEEE Trans Syst Man Cybern*, SMC-9, (1979), nr 1, 62–66

[6] Klette R., Rosenfeld A., Digital Geometry: Geometric Methods for Digital Picture Analysis, *Morgan Kaufmann* (2004)

[7] Rosenfeld A., Distances between fuzzy sets, *Pattern Recognition Letters*, 3 (1985), nr 4, 229–233

[8] Hudelot C., Atif J., Bloch I., Fuzzy spatial relation ontology for image interpretation, *Fuzzy Sets and Systems*, 159 (2008), nr 15, 1929–1951

[9] Jackson, J. E., A User's Guide to Principal Components, *John Wiley and Sons,* (1991)

[10] Miyajima K., Ralescu A., Spatial organization in 2D segmented images: Representation and recognition of primitive spatial relations, *Fuzzy Sets and Systems*, 65 (1994), nr. 2-3, 225–236

[11] Miyajima K., Ralescu A., Spatial organization in 2d images, in *of Proceedings of the 3rd IEEE Conference on Fuzzy Systems* 1 (1994) 100–105

[12] Bloch I., Ralescu A., Directional relative position between objects in image processing: A comparison between fuzzy approaches, *Pattern Recognition*, 36 (2003), nr 7, 1563–1582

[13] Setnes M., Babuska R., Kaymak U., and von Nauta Lemke H. R., Similarity measures in fuzzy rule base simplification, *IEEE Trans Syst Man Cybern B Cybern*, 28 (1998), nr 3, 376–386

[14] Dubois D. J., Prade H., Fuzzy Sets and Systems: Theory and Applications, *Academic Press* (1980), New York