Springer
Berlin
Heidelberg
New York
Barcelona
Hong Kong
London
Milan
Paris
Singapore
Tokyo

Franc Solina   Aleš Leonardis (Eds.)

Computer Analysis of Images and Patterns

8th International Conference, CAIP'99
Ljubljana, Slovenia, September 1-3, 1999
Proceedings

Springer

Series Editors

Gerhard Goos, Karlsruhe University, Germany
Juris Hartmanis, Cornell University, NY, USA
Jan van Leeuwen, Utrecht University, The Netherlands

Volume Editors

Franc Solina
Aleš Leonardis
Faculty of Computer and Information Science
Tržaška cesta 25, 1001 Ljubljana, Slovenia
E-mail: {franc/alesl}@fri.uni-lj.si

Cataloging-in-Publication data applied for

Die Deutsche Bibliothek - CIP-Einheitsaufnahme

Computer analysis of images and patterns : 8th international conference ; proceedings / CAIP '99, Ljubliana, Slovenia, September 1 - 3, 1999. Franc Solina ; Aleš Leonardis (ed.). - Berlin ; Heidelberg ; New York ; Barcelona ; Hong Kong ; London ; Milan ; Paris ; Singapore ; Tokyo : Springer, 1999
(Lecture notes in computer science ; Vol. 1689)
ISBN 3-540-66366-5

CR Subject Classification (1998): I.4, I.5, I.3.3, I.3.7, J.2

ISSN 0302-9743
ISBN 3-540-66366-5 Springer-Verlag Berlin Heidelberg New York

This work is subject to copyright. All rights are reserved, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, re-use of illustrations, recitation, broadcasting, reproduction on microfilms or in any other way, and storage in data banks. Duplication of this publication or parts thereof is permitted only under the provisions of the German Copyright Law of September 9, 1965, in its current version, and permission for use must always be obtained from Springer-Verlag. Violations are liable for prosecution under the German Copyright Law.

© Springer-Verlag Berlin Heidelberg 1999
Printed in Germany

Typesetting: Camera-ready by author
SPIN: 10704452 06/3142 – 5 4 3 2 1 0 Printed on acid-free paper

Preface

This volume presents the articles accepted for the 8th International Conference on Computer Analysis of Images and Patterns (CAIP'99), held in Ljubljana, Slovenia, 1–3 September 1999. The CAIP series of conferences started 14 years ago in Berlin. The series served initially as a forum for meetings between scientists from Western and Eastern-bloc countries. Political circumstances have changed dramatically since the inception of the conference and such contacts are fortunately no longer subject to obstacle. While CAIP conferences are still rooted in Central Europe, they now attract participants from all over the world.

We received 120 submissions, which went through a thorough double blind review process by the program committee members who, had the option of assigning additional reviewers. The final program consists of 47 oral and 27 poster presentations, with authors from 25 different countries. The proceedings also include 2 of the 5 invited lectures given at the conference.

In the name of the steering committee we would like to thank the program committee members and the additional reviewers for their time and efforts. Our thanks also go to the authors for their cooperation and meeting of all deadlines. Most of the communication with the authors and reviewers was done through the World Wide Web. This was made possible by the dedicated work of our conference web master, Bor Prihavec. We thank the International Association for Pattern Recognition for taking CAIP'99 under its wing, the Faculty of Computer and Information Science at University of Ljubljana for hosting the conference, and the industrial and institutional sponsors for giving financial support. Our thanks also go to Springer-Verlag Heidelberg for publishing the CAIP'99 proceedings in the LNCS series. Finally, we thank the local organizers for their commitment, which made the conference possible.

Ljubljana, June 1999

Franc Solina and Aleš Leonardis
Program Co-Chairs
CAIP'99

Organization

CAIP'99 is organized by the Faculty of Computer and Information Science, University of Ljubljana, Slovenia.

Conference Co-Chairs

Franc Solina, University of Ljubljana, Slovenia
Aleš Leonardis, University of Ljubljana, Slovenia

Steering Committee

Chair: G. Sommer (Christian-Albrechts-University of Kiel, Germany)
D. Chetverikov (Computer and Automation Research Institute, Budapest, Hungary)
V. Hlaváč (Czech Technical University, Prague, Czech Republic)
R. Klette (University of Auckland, New Zealand)
F. Solina (University of Ljubljana, Slovenia)

Program Committee

S. Ablameyko, Belarus
J. Arnspang, Denmark
R. Bajcsy, USA
I. Bajla, Slovakia
A. M. Bruckstein, Israel
V. M. Chernov, Russia
D. Chetverikov, Hungary
A. Del Bimbo, Italy
J.-O. Eklundh, Sweden
V. Hlaváč, Czech Republic
J. Kittler, United Kingdom
R. Klette, New Zealand
W. G. Kropatsch, Austria
A. Leonardis, Slovenia (Co-Chair)
R. Mohr, France
M. Schlesinger, Ukraine
W. Skarbek, Poland
F. Solina, Slovenia (Co-Chair)
G. Sommer, Germany
L. Van Gool, Belgium
M. A. Viergever, Netherlands
S. W. Zucker, USA

Reviewers

Sergey Ablameyko
Jens Arnspang
Ruzena Bajcsy
Ivan Bajla
Alberto Del Bimbo
Horst Bischof
Alfred M. Bruckstein
Jörg Bruske
Thomas Bülow
Vladimir M. Chernov
Dmitry Chetverikov
Marina A. Chichyeva
Carlo Colombo
Kostas Daniilidis
Jan-Olof Eklundh
Roman Englert
James Gee
Roland Glantz
Václav Hlaváč
Josef Kittler
Reinhard Klette
Reinhard Koch
Stanislav Kovačič
Walter G. Kropatsch
Norbert Krüger
Jiri Matas
Roger Mohr
Theo Moons
Jane Mulligan
Vladislav Myasnikov
Tomáš Pajdla
Pietro Pala
Josef Pauli
Franjo Pernuš
Marc Pollefeys
Long Quan
Radim Šára
Caterina Saraceno
Michail Schlesinger
Władysław Skarbek
Gerald Sommer
Peter Sturm
Tomáš Svoboda
William Triggs
Tinne Tuytelaars
Alexander Tuzikov
Luc Van Gool
Maarten Vergauwen
Enrico Vicario
Max A. Viergever
Steven W. Zucker

Local Organization

Conference Web Master: Bor Prihavec
Computing Facilities: Aleš Jaklič
Local Arrangements: Bojan Kverh
Igor Lesjak
Jasna Maver
Peter Peer
Danijel Skočaj

Sponsoring Organizations and Institutions

International Association for Pattern Recognition (IAPR)
Slovenian Pattern Recognition Society
IEEE Slovenia Section
Ministry of Science and Technology, Republic of Slovenia
Hermes SoftLab

Table of Contents

Invited lecture

Poster session I

Object and face recognition

Classification and fitting

3D reconstruction and shape representation

Motion

Range image registration

Applications

Invited lecture

Poster session II

Shape from shading, texture and stereo

Real-time tracking

Panoramic images

Spectro-Spatial Gradients for Color-Based Object Recognition and Indexing

Daniel Berwick and Sang Wook Lee

University of Michigan, Ann Arbor MI 48109-2110, USA,
`{dberwick, swlee}@eecs.umich.edu`

Abstract. This paper presents illumination pose- and illumination color-invariant color feature descriptors for object recognition and indexing which are derived from spectral (color) and spatial derivatives of logarithmic image irradiance. While the use of spatial gradients and spatial ratios of image irradiance have been suggested for limited viewing-pose invariance and illumination-color invariance, respectively, gradients in the spectral direction and combination of spectral and spatial gradients have not been fully investigated. We present a unified framework for analyzing spatial and spectral gradients of logarithmic image irradiance, and suggest that spectro-spatial gradients have rich potential for developing local and global descriptors of object color. Experimental results are presented to demonstrate the efficacy of the proposed descriptors.

1 Introduction

Recognition/indexing approaches have recently emerged that do not explicitly use object geometry and shape, but instead rely on object appearances or collections of photometric features such as color, texture and local image variation [6][14]. While the importance of shape and geometry is not diminishing, the feature-collection methods are gaining popularity because of their efficiency especially for content-based image retrieval.

Color is a powerful cue when objects are distinguishable by their distribution of color reflectances. The earliest approach for recognizing objects based on their color distributions was developed by Swain and Ballard [18], and most of the content-based image retrieval systems use color distribution as a primary cue [6]. Color information is highly susceptible to illumination conditions. To effectively employ color information as a reliable descriptor of an object, color reflectance intrinsic to the object surface must be extracted. Variation of color appearance due to object shape, viewing and illumination pose, illumination color, and specularity needs to be discounted. The knowledge gained through color constancy research [4][7][11][13] is reflected in recent recognition/indexing methods that explore illumination color-invariant descriptors [8][9][15][17].

Most of the previous work focuses on finding feature descriptors invariant to illumination color. These approaches assume the color features used are located on 2-D planar surfaces, or the illumination pose is fixed for 3-D objects. Only recently has the issue of illumination-pose invariance been explicitly addressed,

2D Motion Analysis by Fuzzy Pattern Comparator

Mirjana Bonković, Darko Stipaničev, Maja Štula

LaRIS-Laboratory for Robotics and Intelligent Systems
Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture
UNIVERSITY OF SPLIT
R.Boskovica bb, 21000 SPLIT, C r o a t i a
Web: http://zel.fesb.hr/laris
e-mail: mirjana@fesb.hr, dstip@fesb.hr

Abstract.

The motion analysis plays an important role in the broad range of applications, such as visual feedback control, scene reconstruction and similar. In this paper the technique for 2D-motion analysis based on displacement vector determination is described. In our approach we have used the device called Fuzzy Pattern Comparator (FPC) and develop the fuzzy algorithm based on novel, cylindrical fuzzy sets of directions. Their introduction made the calculation of displacement vector direction and magnitude quite simple. The method was verified experimentally and used in final positioning of the robot arm.

1 Introduction

Displacement vector field [1], [2] which can be defined as a mapping between one frame from an image sequence and the proceeding or following frame is of the great importance in motion analysis, for applications such as visual feedback control [3] or scene reconstruction [4]. Existing techniques for image matching roughly fall into two categories: continuous and discrete.

In the *continuous approaches*, the interframe motion is approximated by motion velocity and the displacement vectors are given as optical flow [2].

The *discrete approach* techniques treat the images as samples of the scene taken at discrete times. Scene features of interest such as high gray value variations, edges, lines or intensity patterns, are extracted from the images and matched appropriately. The procedure is usually based on sophisticated techniques for overlapping recognized shapes in a sequence of analyzed images [5], [6].

The concept of fuzzy sets fits very naturally in the framework of discrete image matching techniques, so we have used for object displacement vector determination the fuzzy correlation method based on Fuzzy Pattern Comparator (FPC) board.

The procedure had two phases:

- the learning phase, and
- the working phase.

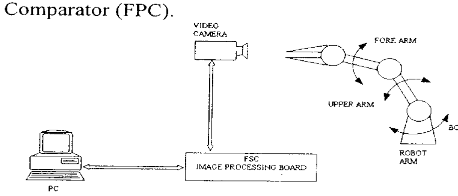
In the *learning phase* the robot was positioned up, down, up-left, up-right, down-left and down-right according to its desired, final position (the camera's central point) and appropriate images were captured and saved in external pattern memories.

In the *working phase*, when the robot has entered in the camera's image field, the displacement vectors of its motion were determinate in real time, taking into account the differences between its image and the images of its displacements, saved in the external pattern memories. The displacement vectors directions and magnitudes were calculated by fuzzy algorithm based on cylindrical fuzzy sets of direction. These values were used as input to robot control algorithm which have moved the robot gripper toward its desired, final position (the camera's central point).

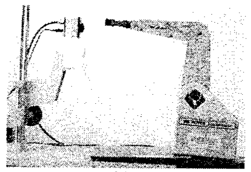
2 System Overview

The system consists of the robot arm, video camera, FPC board and a personal computer (486, 66MHz) as Fig.1a). shows. The robot arm (type MICROBOT TeachMover) was equipped with motorized jaw-type gripper, which was in our experiments always in horizontal position. The camera was mounted in front of the robot arm as Fig1b). shows. The main control task of this visual feedback control system was to guide the robot arm until the gripper takes the predefined central position in the camera's image.

The used equipment was more or less standard one, except the Fuzzy Pattern Comparator (FPC).



a)



b)

Fig. 1. a) Experimental system setup b) Photo of the experimental system

FPC is s specialized device particularly designed to provide very fast comparison of frames of data. The FPC utilizes fuzzy logic's method of comparing data in order to determine the similarities or differences in groups of data.

Data is entered serially into the device, where it is formatted into bit fields and compared, one field at a time, with data stored in external pattern memories. In our case the input data where the live image from the video camera. Each input image frame was stored in the first pattern memory and compared with six predefined pattern images stored in external pattern memories during the learning phase. Each pattern memory has a register where results of comparison were stored. The smallest value indicates that the input data due the most clearly matched to its appropriate stored pattern.

3 The Learning Procedure

During the learning phase, robot arm is moved in front of the camera. Its six characteristic position (Fig.2.) viewed by the fixed camera (up, right-up, right-down, down, left-down and left-up) were captured and stored in six FPC board external pattern memories. In working phase a comparison was made between the data from a new image of a scene with data stored in the external pattern memories. Each difference between pixels with the same xy coordinate from stored and captured images has increased the value of the register accompanied to that pattern memory. The final result was an accumulation of errors across the all image elements. Consequently, if two images differ from each other in all the image elements, the value of the register accompanied to the pattern memory have been 192x132=25344 because the input image was digitalised in 192x132 pixels.

Contrary, for two identical images the register will have zero value. These facts were used for displacement vector determination described in the following section.

4 Displacement Vector Determination

The displacement vector is determined by the three-step procedure. The first one is *calculation of the degrees of fulfillment* between the input scene and stored displaced images in memories. Each displace image has its own degree of fulfillment, which is reciprocal to the error sums. If an error sum is equal to zero, then the stored pattern is identically equal to the compared one. Therefore, the degree of fulfillment has maximum value, which is equal to 1.

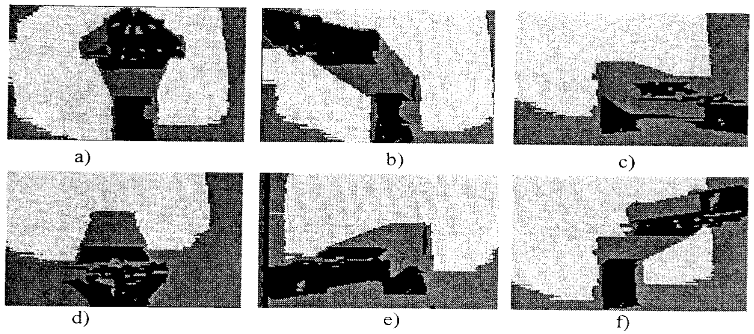


Fig. 2. Images of the predefined displacements: a) up, b) left-up, c) right-down, d) down, e) left-down and e) right-up

Contrary, the highest value of an error sum means the weakest match between captured and stored patterns, resulting with zero degree of fulfillment. Consequently, the overall degree of fulfillment is a 6-element vector $\vec{\lambda} = [\lambda_1\ \lambda_2\ \lambda_3\ \lambda_4\ \lambda_5\ \lambda_6]$, whose elements are calculated using the equations

$$\textit{if} \quad E_i = max\ Err \quad \lambda_i = 0 \tag{1}$$

$$\textit{else if} \quad E_i = min\ Err \quad \lambda_i = 1 \tag{2}$$

$$\textit{else}\ \lambda_i = \frac{E_i - minErr}{maxErr - minErr} \tag{3}$$

where maxErr is the maximal error sum and minErr is minimal error sum between input image and displaced images stored in pattern memories. In our case minErr was 0 and maxErr = 25344. The degree of fulfillment λ_1 corresponds to the displace image "up", λ_2 to "right-up", λ_3 to "right-down", λ_4 to "Down", λ_5 to "left-down", λ_6 to "left-up".

The second step is *determination of the displacement vector output fuzzy set*. For this purpose we have introduced cylindrical fuzzy sets of direction depicted on Fig.3.

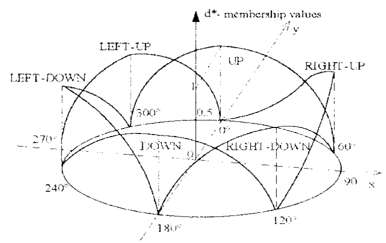


Fig. 3. Cylindrical fuzzy sets of direction.

As Fig.3. shows the definition set of cylindrical fuzzy sets of direction is a circle of directions from 0° to 360°. Membership functions have their maximal value 1 at 0, 60, 120, 180, 240 and 300 degrees for "up", "right-up", "right-down", "down", "left-down" and "left-up" directions.

The output displacement vector fuzzy set is determined using the fuzzy composition

$$d^* = \bigvee_i (\lambda_i \wedge d_i^*) \tag{4}$$

Where λ_i is the degree of fulfillment for the *i*-th displacement image (up, right-up, etc...) and d_i^* is its corresponding fuzzy sets of direction. If, for example, the captured robot arm position is identically equal to the displacement image called right-up, its overall degree of fulfillment will be

$$\vec{\lambda} = [0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0] \tag{5}$$

and its corresponding output fuzzy sets are shown on Fig.4a). Similarly if the robot arm on the input image is positioned somewhere between "left-down" and "left-up" as image 6a) shows, the overall degree of fulfillment will be

$$\vec{\lambda} = [0 \quad 0 \quad 0 \quad 0 \quad 0.2 \quad 0.8] \tag{6}$$

and corresponding output displacement vector fuzzy set is shown on Fig.4b).

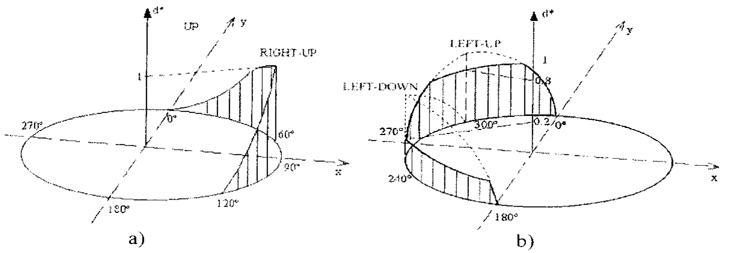


Fig. 4. The shape of the output displacement vector fuzzy sets:

a) for $\vec{\lambda} = [0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0]$

b) for $\vec{\lambda} = [0 \quad 0 \quad 0 \quad 0 \quad 0.2 \quad 0.8]$

The final, third stage is *the interpretation of the output displacement vector fuzzy set* which results in displacement vector direction and magnitude. The displacement vector is defined inside the circle of directions, which is the definition set of cylindrical fuzzy sets of direction. The displacement vector always starts from the circle center and its end point (x_d,y_d) is defined by the center of gravity of the output displacement vector fuzzy set, calculated by formulas:

$$x_d = \frac{\sum_{d=0}^{360} d * d^*(d)\cos(d)}{\sum_{d=0}^{360} d^*(d)} \tag{7}$$

$$y_d = \frac{\sum_{d=0}^{360} d * d^*(d)\sin(d)}{\sum_{d=0}^{360} d^*(d)} \tag{8}$$

$$|d| = \sqrt{x_d^2 + y_d^2} \tag{9}$$

$$d_\varphi = atan\frac{y_d}{x_d} \tag{10}$$

where d*(d) is the value of the output displacement vector fuzzy set membership function for direction d. |d| is the magnitude of the displacement vector and d_φ is its direction. Fig.5a). shows the example for the output displacement vector fuzzy set from the Fig.4b).

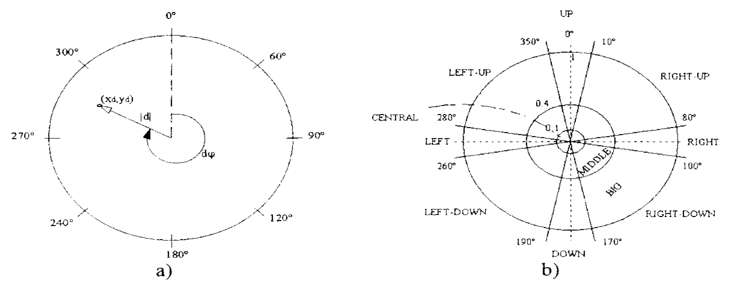


Fig. 5. a) Displacement vector for output displacement vector fuzzy set for Fig.4b). b)Definition of linguistic terms used in linguistic if-then rules (left-up, left-down, down, right-down, right, right-up, up, central, middle and big)

5 Control of Robot Arm

The robot arm used in experiment was of RRR type (educational robot MICROBOT TechMover) schematically shown in Fig.1a). For its 2D movement according to camera's optical center, only two robot segments were moved: robot BODY and ELBOW, because the workspace was limited by the camera's field of view. The space viewed by the camera was divided in sections as Fig.5b). shows. There were eight direction formed by four lines crossing through center "S" and three magnitude sections (central, middle and big) formed by three concentric circles. Based on these lines and circles, two linguistic variables were introduced: distance from the center of the image (MAGNITUDE) and displacement position (DIRECTION). The control algorithm was defines by simple linguistic if-then rules:

If DIRECTION is *left*, then move robot segment BODY to the *right*.
If DIRECTION is *left-up*, then move robot segment BODY to the *right*, and robot segment ELBOW to the *down. etc.*

All together 8 linguistic rules were used. Also, as the robot arm was controlled by the step motors, it was possible to control the number of steps for faster achieving the central position and three additional rules were introduced:

If MAGNITUDE is CENTRAL then STOP.
If MAGNITUDE is MIDDLE then NUMBER_OF_STEPS is 1.
If MAGNITUDE is BIG then NUMBER_OF_STEPS is 4.

In each iteration step, the if part of rules were tested and appropriate control action (incremental movement of robot segments) were applied.

6 Experimental Results and Conclusions

The robot positioning experiment confirmed our theoretical expectations. Using our FPC based image displacement vector determination system the robot was controlled in real time. Fig.6. and 7. shows one of experiments. For the robot starting position shown on Fig.6a) the displacement vector direction and magnitude were 200° and 0.4. Fig.6b) shows the final image. Although quite big oscillations in direction determination were noticed (mostly introduced by the unstable camera capturing characteristic) the arm was very precisely positioned from starting to the final position.

a) b)

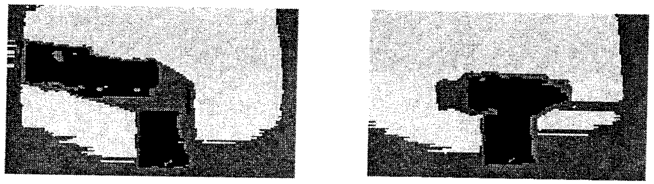


Fig. 6. a) The starting image b) The image of final positioned robot arm

This system insensibility is mostly due to fuzzy algorithms used in displacement vector detection. Fig.7. shows the measurement results:

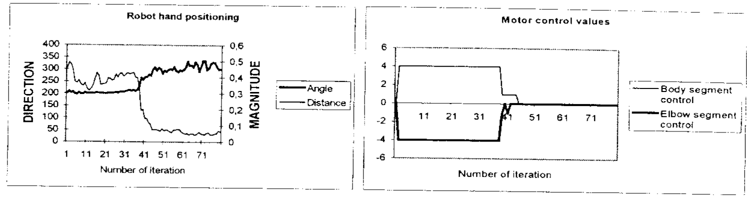


Fig. 7. Experiment results of fuzzy robot arm positioning based control: Displacement vector direction and magnitude and motor control values. (no. of steps in each iteration).

Our experiment shows that quite inexpensive equipment could be used for not so simple control tasks based on image pattern recognition. The limitation of the system was 4-bit image digitalization, as Fig.2. and Fig.6. shows. In the future we intend to use more precise digitalization unit and to improve our system introducing the possibility for robot arm orientation recognition. The second task could be achieved using additional pattern memories. Also, we intend to break the limits in robot workspace limitations, and develop the system for 3D vector displacement determination.

References

[1] Hans-Helmut Nagel, W. Enkelmann: An Investigation of Smoothness Constraints for the Estimation of Displacement Vector Fields from Image Sequences, in book **Computer Vision Principles**, pp. 498-526, Eds. R. Kasturi and R. C. Jain, IEEE Computer Society Press, 1991

[2] B. K. P. Horn: **Robot Vision**, MIT Press, 1981.

[3] Peter I. Corlee, **Visual Control of Robots**, John Wiley&Sons Inc., 1996

[4] J. J. Weng: 3D Motion Analyses from Image Sequences Using Point Correspondences, from **Handbook of Pattern Recognition and Computer Vision**, pp. 395-441, Eds. C. H. Chen, L. F. Pau, P. S. P. Wang, Worlds Scientific, Publishing Company, 1993.

[5] Bernd Jahne: **Digital Image Processing**, Springer-Verlog, 1991.

[6] A. K. Jain: **Fundamentals of Digital Image Processing**, Prentice Hall International Editions, 1989.

[7] **Fuzzy Set Comparator** (MD1210), Micro Devices, USA, 1989.

Acknowledgements

This work was supported by Ministry of Science and Technology of Republic of Croatia through Main Project: *"Complex System Control by Intelligent Methods"* and its Minor Projects.