Soft Computing Based Point Correspondence Matching for Automatic 3D Reconstruction

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Abstract: In computer vision image point correspondence matching plays an important role. With the help of the point correspondence matching algorithms for example some of methods concerning the field of stereo vision can be automatized. This paper presents a method for quickly and reliably selecting and matching of the most interesting image points (feature points).

Keywords: Feature points, image point correspondence, 3D modeling, noise cancellation, edge detection, corner detection, fuzzy reasoning

1   Introduction

Feature matching is a key component in many computer vision applications, for example in stereo vision, motion tracking, and identification. The most significant problem in stereo vision is how to find the corresponding points in two, let us call them left and right images, referred to as the correspondence problem. In the field of computer vision several applications require to match feature points of images taken form different camera positions. Stereo techniques can be distinguished by several attributes, e.g., whether they use area-based or feature-based techniques, are applied to static or dynamic scenes, use passive or active techniques, or produce sparse or dense depth maps. The extremely long computational time needed to match stereo images is still the main obstacle on the way to the practical application of stereo vision techniques. In applications such as robotics, where the environment being modeled is continuously changing, these operations must also be fast to allow a continuous update of the matching set, from which 3D information is extracted [1] [2]. The correspondence search in stereo images is commonly reduced to significant features as computing time is still an important criterion in stereo vision. There exist several stereo vision techniques, from which

the most popular are the Area-based and the Feature-based stereo techniques. The first kind of the mentioned techniques finds corresponding points based on the correlation between the corresponding areas in left and right images [3]. First, a point of interest is chosen in one of the images. A correlation measure is then applied to search for a corresponding point with a matching neighborhood in the other image. Area-based techniques have the disadvantage of being sensitive to photometric variations during the image acquisition process and are sensitive to distortions, which reason in the first place is the changing viewing position. Feature-based stereo techniques, on the other hand, match features in the left image to those in the right image. Features are selected as the most prominent parts in the image, such as, for example, edge points or edge segments, corner points etc. Feature-based techniques have the advantage of being less sensitive to photometric variations and of being faster than the area-based stereo method, because there are fewer candidates for matching corresponding points [4]. If we combine the Area-based stereo techniques with the Feature-based stereo techniques we can get better results. In this paper a new approach of feature points correspondence matching is presented. The paper is organized as follows: In Section 2 the preprocessing phase of the input pictures is detailed, Section 3 shows how to find edge and corner points, while Section 4 presents the matching algorithm of these feature points. In Section 5 experimental results are summarized and Section 6 is devoted to the conclusions.

2   Preprocessing of the Images, Noise Elimination

A major task in the field of digital processing of measurement signals is to extract information from sensor data corrupted by noise [5] [6]. For this purpose we will use a special fuzzy system characterized by an IF-THEN-ELSE structure and a specific inference mechanism. Different noise statistics can be addressed by adopting different combinations of fuzzy sets and rules [5] [6]. Let $x(\mathbf{r})$ be the pixel luminance at location $\mathbf{r}=[r_1, r_2]$ in the noisy image where r_1 is the horizontal and r_2 the vertical coordinate of the pixel. Let $\mathbf{N}$ be the set of eight neighboring pixels (see Fig. 1a). The input variables of the fuzzy filter are the amplitude differences defined by:

$$\Delta x_j = x_j - x_0, j = 1,...,8 \tag{1}$$

where the x_j, $j=1,\dots,8$ values are the neighboring pixels of the actually processed pixel x_0 (see Fig. 1a).

X_1	X_2	X_3
X_4	X_0	X_5
X_6	X_7	X_8

Figure 1a

The neighboring pixels of the actually processed pixel x_0
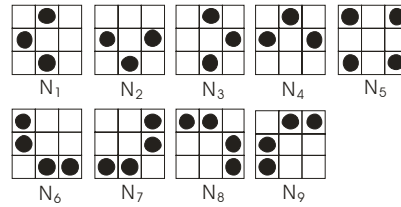

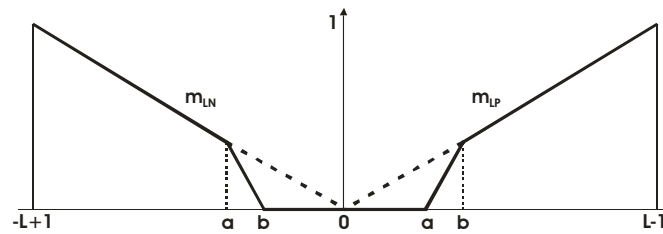Figure 1b

Pixel patterns $N_1,...,N_9 \subseteq N$

Figure 2

Membership function m_{LP}. Parameters a and b are appropriate constant values

Let y_0 be the luminance of the pixel having the same position as x_0 in the output signal. This value is determined by the following relationship:
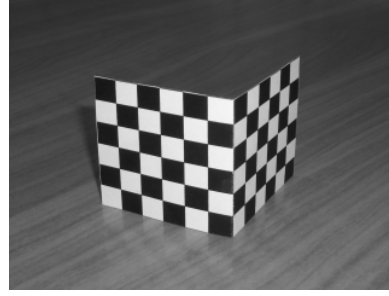
$$y_0 = x_0 + \Delta y \tag{2}$$

where Δy is calculated thereinafter (see eq. (5)). Let the rule-base deal with the pixel patterns $N_1,...,N_9 \subseteq N$ (see Fig. 1b).
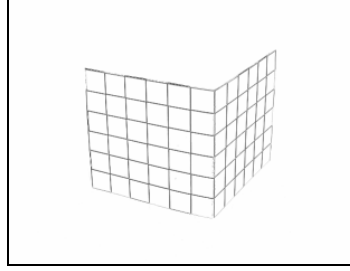
The value y_0 can be calculated, as follows [7]:

$$\lambda = MAX\left\{MIN\left\{m_{LP}(\Delta x_j) : x_j \in N_i\right\}; i = 1,...,9\right\} \tag{3}$$
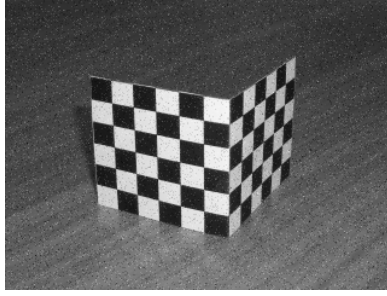
3a   3b

3c

Figure 3a represents the image corrupted by impulse noise, 3b shows the image after fuzzy filtering and in figure 3c the image after the fuzzy based edge detection can be followed

$$\lambda^* = MAX\left\{MIN\left\{m_{LN}(\Delta x_j) : x_j \in N_i\right\}, i = 1,...,9\right\} \tag{4}$$

$$\Delta y = (L-1)\Delta\lambda$$
$$y_0 = x_0 + \Delta y \tag{5}$$

where $\Delta\lambda = \lambda - \lambda^*$, m_{LP} and m_{LN} correspond to the membership functions of fuzzy sets large positive and large negative and $m_{LP}(u)=m_{LN}(-u)$ (see Fig. 2). The filter is recursively applied to the input data. Using this fuzzy filter the impulse noise can effectively be eliminated. With the help of the parameters *a, b* the sensitivity of the noise elimination method can be modified, i.e., the shape of the membership functions m_{LN} and m_{LP} can be tuned. If after the noise cancellation noisy image points will remain in the image, they will also be detected as corner points in the next step (see Section 3) and therefore it is very advisable to eliminate them as effectively as possible. Otherwise, for example at one hand, at automatic 3D reconstruction of a scene these non eliminated noisy pixels will appear in the 3D space, as well and on the other hand, the efficiency of the point correspondence matching algorithms will brake down with the number of non-eliminated noisy pixels.

3 Detection of Feature Points

Edge detection in an image is a very important step for a complete image understanding system. In fact, edges correspond to object boundaries and are therefore useful inputs for 3D reconstruction algorithms. The proposed fuzzy based edge detection [7] can very advantageously be used for this purpose.

Let $x_{i,j}$ be the pixel luminance at location $[i,j]$ in the input image. Let us consider the group of neighboring pixels which belong to a 3x3 window centered on $x_{i,j}$ (see Fig. 1a). The output of the edge detector is yielded by the following equation [7]:

$$z_{i,j} = (L-1)MAX\{m_{LA}(\Delta y_1), m_{LA}(\Delta y_2)\}$$

$$\Delta y_1 = \left| x_{i-1,j} - x_{i,j} \right|$$

$$\Delta y_2 = \left| x_{i,j-1} - x_{i,j} \right|$$

(6)

where $z_{i,j}$ is the pixel luminance in the output image and m_{LA} is the used membership function (see Fig. 4). Pixels $x_{i-1,j}$ and $x_{i,j-1}$ are the luminance values of the left and the upper neighbors of the pixel at location $[i,j]$.

The fuzzy based technique compared to the classical methods provided better results with less (very small) processing time. Fig. 3 shows an example for the filtering and edge detection results. In Fig. 3a the original photo corrupted by noise can be seen, Fig. 3b presents the filtered image of Fig. 3a, while in Fig. 3c the result of the edge detection can be followed.

Corners are also local image features and are very useful at the 3D reconstruction of a scene. Using these feature points the processing time of the reconstruction of a scene can be reduced.
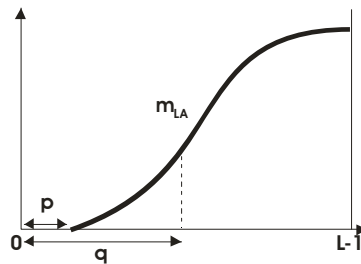

Figure 4

Membership function m_{LA}. Parameters p and q are appropriate constant values with the help of which the membership function m_{LA} can be shaped. Parameter q is for changing the curvature of the membership function and p is for setting the sensitivity of the proposed edge detector

Any corner detection algorithm should satisfy the following requirements:

- All the true corners should be detected

- No false corners should be detected

- Corner points should be well localized

- Corner detector should be robust with respect to noise

Förstner determines corners as local maxima of function $H(x,y)$ [8]:

$$H(x,y) = \frac{\left(\frac{\partial I}{\partial x}\right)^2 \left(\frac{\partial I}{\partial y}\right)^2 - \left(\frac{\partial I}{\partial x}\frac{\partial I}{\partial y}\right)^2}{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2} \, , \tag{7}$$

where $I(x,y)$ is the intensity function and x, y are the coordinates of the pixels in the image. Starting from the algorithm of Förstner a new, improved corner detection algorithm can be developed by combining it with fuzzy reasoning. This can be used for the characterization of the continuous transition between the localized and not localized corner points, as well. The algorithm consists of the following steps: First, the picture, in which we have to find the corners, is preprocessed. As a result of the preprocessing procedure the noise is eliminated. For this purpose we apply the above described fuzzy filter [5] [6]. After noise-filtering, the first derivatives of the intensity function $I(x, y)$ are calculated in each image point. This is solved by using the following convolution masks:

$$\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$ for the determination of $\dfrac{\partial I}{\partial x}$ and

$$\begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$ for determining $\dfrac{\partial I}{\partial y}$.

Table 1

Comparison some of corner detectors with fuzzy based one

	Correctly detected corners [%]	Incorrectly detected points [%]	Non detected points [%]
Fuzzy based corner detector	84	3,2	16
SUSAN corner detector	52	4,7	48
Harris corner detector k=0.001	71	15,3	29

For increasing the effectiveness of the corner detection it is proposed to smooth the entries I_x^2, I_y^2, I_xI_y in eq. (7), (I_x and I_y stand for the first partial derivatives of the intensity function $I(x,y)$, x,y denote the 2D coordinates of the pixels). This can be done by applying a Gaussian 6x6 convolution kernel with $\sigma=1$ [8]. As the following step, the values $H(x,y)$ are calculated for each image point with the help of the previously determined smoothed I_x^2, I_y^2, and I_xI_y values. If the detected corners are neighbors, we should keep only the corner having the largest calculated value $H(x,y)$. The others are to be ignored. In most of the cases we can not unambiguously determine whether the analyzed image point is a corner or not based only on a certain concrete threshold value, therefore we have introduced fuzzy techniques in the inference of the proposed corner detection algorithm. As a result, the rate of the corner detection has been improved (see Table 1). By the score of the membership function of fuzzy set "corners" (see Fig. 5) we can determine a weighting factor, which characterizes "the rate of being a corner". The value of the membership function m_c is 1 for those image points for which the calculated value H equals or is larger than the given threshold value. With the help of the parameters p and q (see Fig. 5) the shape of the membership function can be modified and so the sensitivity of the described detector can be changed. Finally, the output of the proposed corner detector is yielded by the following relation:

$$C_{x,y} = (L-1)m_c(H),\qquad\qquad\qquad\qquad\qquad (8)$$
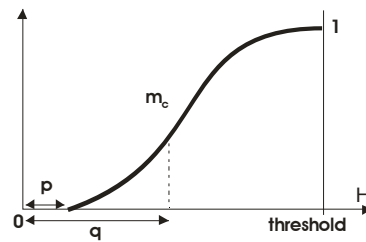
Figure 5

Membership function of fuzzy set "corners" (m_c). Axis H is the axis of the calculated $H(x,y)$ values. Parameters p and q are appropriate constant values with the help of which we membership function m_c can be shaped: parameter q is for changing the curvature of the membership function and p is for setting the sensitivity of the proposed corner detector.
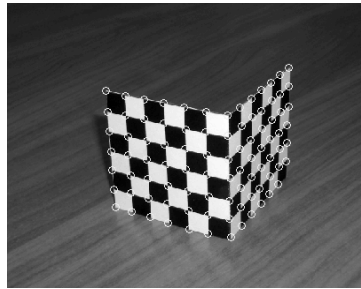
Figure 6

The image after fuzzy based corner detection. The circles indicate the detected corners.

where $C_{x,y}$ represents the gray-level intensity values of the output image, x and y are the horizontal and vertical coordinates of the processed image point, L is the largest gray level intensity value, and H stands for the calculated $H(x,y)$ values.

4 Matching the Corresponding Feature Points in Stereo Images

Feature matching is commonly referred to as the correspondence problem. The problem is how to automatically match corresponding features from two images, while at the same time not assigning matches incorrectly. The common approach for corners, is to take a small region of pixels around the detected corner (referred to as a correlation window) and compare this with a similar region around each of the candidate corners in the other image. Each comparison yields a score, a measure of similarity. The match is assigned to the corner with the highest matching score. The most popular measure of similarity is the cross-correlation. Most matching algorithms include constraints to complement the similarity measure. These may take the form of constraints on which corners are selected as candidate matches: a maximum disparity, or corners which agree with some known relationship between the images (such as the epipolar geometry). Constraints such as uniqueness or continuity may also be applied after candidate matches have been found. With the help of the epipolar constraint we can reduce the number of candidate image points. We have to search only along the epipolar line corresponding to the actually chosen image point in the source image. This epipolar line can be determined using the so called fundamental matrix [2]. The fundamental matrix defines a bilinear constraint between the coordinates of the corresponding image points. If for example $\mathbf{m_2}$ is the point in the second image
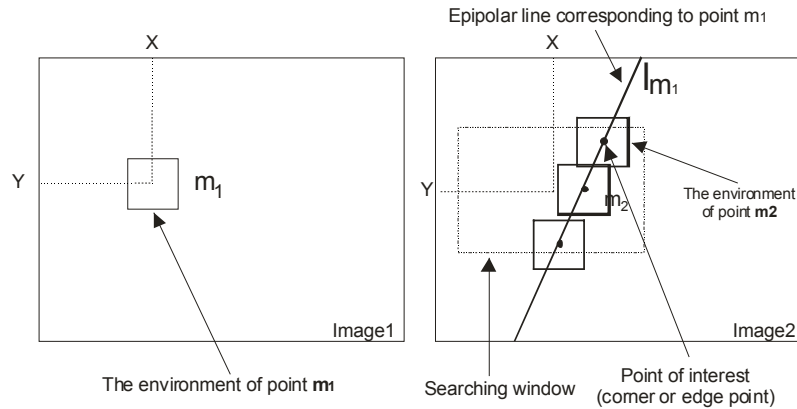

Figure 7
Illustration of the proposed point matching technique. In the left image a chosen corner is illustrated, while in the right image the candidate corner points can be seen.

corresponding to $\mathbf{m_1}$ (see Fig. 7), it must lie on the epipolar line $\mathbf{l_{m1}}$. The epipolar constraint can be written as:

$$\mathbf{m}_2^T \mathbf{F} \mathbf{m}_1 = 0 \tag{9}$$

Linear Solution for the Fundamental Matrix:

Each point match gives rise to one linear equation in the unknown entries of matrix $\mathbf{F}$. The coefficients of this equation can easily be written in terms of the known coordinates of $\mathbf{m_1}$ and $\mathbf{m_2}$. Specifically, the equation corresponding to a pair of points $\mathbf{m_1}$ and $\mathbf{m_2}$ will be

$$xx'f_{11} + xy'f_{12} + xf_{13} + yx'f_{21} + \\ yy'f_{22} + yf_{23} + x'f_{31} + y'f_{32} + f_{33} = 0 \tag{10}$$

where the coordinates of $\mathbf{m_1}$ and $\mathbf{m_2}$ are $(x, y, 1)^t$ and $(x', y', 1)^t$, respectively. Combining the equations obtained for each match gives a linear system that can be written as $\mathbf{Aw = 0}$, where $\mathbf{w}$ is a vector containing the 9 coefficients of $\mathbf{F}$ (f_{ij}) and each row of $\mathbf{A}$ is built of the coordinates $\mathbf{m_1}$ and $\mathbf{m_2}$ of a single match. Since $\mathbf{F}$ is defined only up to an overall scale factor, we can restrict the solution for $\mathbf{w}$ to have norm 1. We usually have more than the minimum number (8) of points, but these are perturbed by noise so we will look for a least squares solution:

$$\min_{\|\mathbf{w}\|=1} \|\mathbf{Aw}\|^2 \tag{11}$$

As $\|\mathbf{Aw}\|^2 = \mathbf{w}^T \mathbf{A}^T \mathbf{Aw}$, we have to find the eigenvector associated with the smallest eigenvalue of the 9x9 symmetric, positive semidefinite normal matrix $\mathbf{A^T A}$. However, this formulation does not enforce the rank constraint, so a second step must be added to the computation to project the solution $\mathbf{F}$ onto the rank 2 subspace. This can be done by taking the Singular Value Decomposition (SVD) of matrix $\mathbf{F}$ and setting the smallest singular value to zero. Basically, SVD decomposes any real valued matrix $\mathbf{F}$ in the form of

$$\mathbf{F = Q \, D \, R} \tag{12}$$

where $\mathbf{D}$ is diagonal and $\mathbf{Q}$ and $\mathbf{R}$ are orthogonal matrices. Setting the smallest diagonal element of $\mathbf{D}$ to 0 and reconstituting gives the desired result.

As we know, the images in which we have to find the corresponding feature points are taken from different camera positions. If the angle of the camera positions is relatively small, we have greater chance to match the mentioned feature points, because of the small deformation of image pixels between two views. In this case the corresponding points can be found with high reliability in each image. Feature point mentioned in this section can be either corners or edge points. Matches are found by evaluating the similarity between image regions and selecting the match of the pair of regions with the highest similarity (see Fig. 7). There are many

similarity measure definitions known in the literature [10]. In this paper, we introduce a new measure of similarity which is based on the combination of cross-correlation and a fuzzy measure:

$$M_s = \frac{\sum F_m(x,y) I_L(x,y) I_R(x,y)}{\sum F_m(x,y) I_L(x,y)^2 \sum F_m(x,y) I_R(x,y)^2} , \qquad (13)$$

where I_L and I_R are the intensity functions of the input images (left and right image) and F_m stands for the fuzzy measure corresponding to the pixel with coordinates x,y. F_m can be calculated, as follows:

$$F_m(x,y) = MIN\{\mu_A(x), \mu_B(y)\}, \qquad (14)$$

μ_A and μ_B are the membership functions in universes X and Y representing the closeness of the points in the environment to the analyzed corner point-candidate (see Fig. 8).
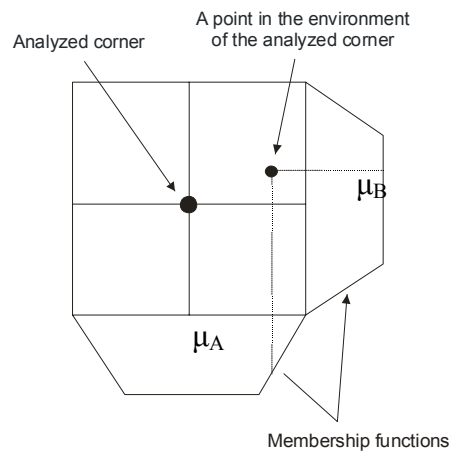

Figure 8
Fuzzy membership functions μ_A and μ_B of closeness used in eqs. 13, 14

5   Experimental Results

Fig. 9 represents two overlapped images, taken form two different camera positions. In the image the point correspondence is illustrated with the help of lines joining the corresponding image points. The end points of the lines represent the corresponding feature points of the overlapped images.

Figure 9
The two images in overlapped form with the corresponding feature points
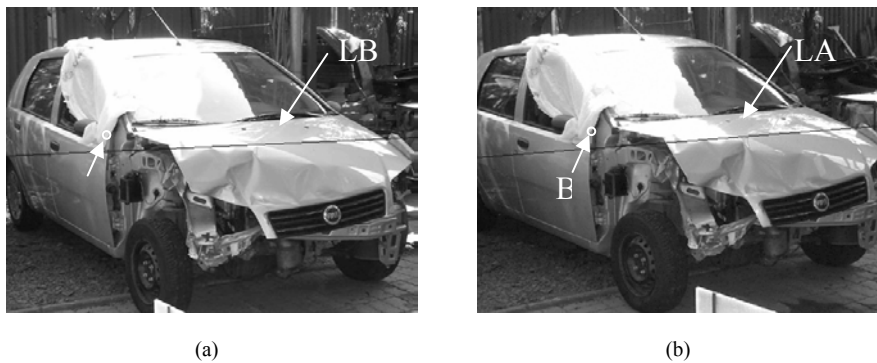
(a)   (b)

Figure 10
The epipolar lines and an example of two corresponding feature points

Fig. 10a and Fig. 10b illustrate two images taken from different camera positions. On each of them an epipolar line corresponding to the pointed image pixel can be followed. To the image point *A* corresponds the epipolar line *LA* and to the image point *B* correspond the epipolar line *LB*. The corresponding image point of *A* is the image point *B* and inversely the point which corresponds to *B* is the image point *A*.

Conclusions

This paper introduces a new fuzzy based method for the matching of corresponding feature points in images, which are taken of the same scene from different camera positions. The method uses fuzzy based noise elimination and feature detection algorithms, with the help of which we can eliminate the non interesting points from the images and detect those feature points, which are the most interesting from the 3D reconstruction point of view. The method combines the area based and the feature based stereo techniques and applies fuzzy reasoning for the determination of a similarity measure, with the help of which we can decide which feature points can be the best candidates of being the corresponding

points. The method introduced in this paper can advantageously be used in many other fields, as well, e.g. in robot guiding, medicine, and 3D object reconstruction.

Acknowledgement

References

[1] Zhang, Z., Deriche, R., Faugeras, O., Luong, Q.-T., "A Robust Technique for Matching Two Uncalibrated Images Through the Recovery of the Unknown Epipolar Geometry," *Artificial Intelligence*, 1995, pp. 87-119

[2] Rövid, A., A. R. Várkonyi-Kóczy, Várlaki, P., "3D Model Estimation from Multiple Images," *IEEE International Conference on Fuzzy Systems, FUZZ-IEEE'2004*, July 25-29, 2004, Budapest, Hungary, pp. 1661-1666

[3] Faugeras, O., Vieville, T., Theron, E., Vuillemin, J., Hotz, B., Zhang, Z., Moll, L., Bertin, P., Mathieu, H., Fua, P., Berry, G., Proy, C., "Real time correlation-based stereo: algorithm, implementations and applications," *Research Report 2013*, INRIA Sophia-Antipolis, France, August 1993, p. 45.

[4] Lee, C.-Y., Cooper, D. B., and Keren, D., "Computing Correspondence Based on Region and Invariants without Feature Extraction and Segmentation," *Proc. CVPR´93*, New York, USA, 1993, pp. 655-656

[5] Russo, F., "Fuzzy Filtering of Noisy Sensor Data," *In Proc. of the IEEE Instrumentation and Measurement Technology Conference*, Brussels, Belgium, 4-6 June 1996, pp. 1281-1285

[6] Russo, F., "Recent Advances in Fuzzy Techniques for Image Enhancement," *IEEE Transactions on Instrumentation and Measurement*, Vol. 47, No. 6, Dec. 1998, pp. 1428-1434

[7] Russo, F., "Edge Detection in Noisy Images Using Fuzzy Reasoning," *IEEE Transactions on Instrumentation and Measurement*, Vol. 47, No. 5, Oct. 1998, pp. 1102-1105

[8] Förstner W., "A feature based correspondence algorithm for image matching," *Int. Arch. Photogramm. Remote Sensing*, vol. 26, 1986, pp. 150-166

[9] Catté, F., Lions, P.-L., Morel, J.-M., Coll, T., "Image selective smoothing and edge detection by nonlinear diffusion," *SIAM Journal on Numerical Analysis*, 32:, 1992, pp. 1895-1909

[10] Bogdan, G., Meer, P., "Point Matching under Large Image Deformations and Illumination Changes*," IEEE Transactions on Pattern Analysis and Machine Intelligence*, VOL. 26, NO. 6, JUNE 2004, pp. 674-688