Open-Ball Scheme을 이용한 2D 패턴의 상대적 닮음 정도 측정의 Moment Invariant Method와의 비교

論 文
48A-1-11

Similarity Measurement Using Open-Ball Scheme for 2D Patterns in Comparison with Moment Invariant Method

金 聖 洙
(Sung-Soo Kim)

Abstract - The degree of relative similarity between 2D patterns is obtained using Open-Ball Scheme. Open-Ball Scheme employs a method of transforming the geometrical information on 3D objects or 2D patterns into the features to measure the relative similarity for object(pattern) recognition, with invariance on scale, rotation, and translation. The feature of an object is used to obtain the relative similarity and mapped into [0, 1] the interval of real line.

For decades, Moment-Invariant Method has been used as one of the excellent methods for pattern classification and object recognition. Open-Ball Scheme uses the geometrical structure of patterns while Moment Invariant Method uses the statistical characteristics. Open-Ball Scheme is compared to Moment Invariant Method with respect to the way that it interprets two-dimensional pattern classification, especially the paradigms are compared by the degree of closeness to human's intuitive understanding. Finally the effectiveness of the proposed Open-Ball Scheme is illustrated through simulations.

Key Words : Pattern Classification, Similarity Measurement, Intuitive Understanding

1. Introduction

Pattern recognition and classification is based on the methodology defined by the metric used in the information space of the patterns. The metric to be used is determined by the characteristics of the information from patterns(objects) which we desire to understand. In the area of machine vision, understanding the characteristics of artificial objects (patterns in 2D and 3D) may be more critical than any other areas. The characteristics of information on a problem pattern influence what metric may be used in obtaining features for classification.

In general, pattern recognition with invariance to position, scale, and orientation is an essential issue in obtaining a unique feature for classification or recognition. Thus, finding efficient invariant features is an important goal in recognition and classification. Open-Ball Scheme(OBS), which is a feature extraction method[1-3] was introduced initially in order to classify three-dimensional objects that approximate real objects. In this paper, the OBS algorithm for feature extraction is compared to Moment Invariant Method[4-8] that has been known as one of the most interesting and attractive algorithms for classification in recent decades. Moment invariants are the global features of an image in pattern recognition, image classification, target identification and in various areas. Feature-based recognition of objects or patterns independent of their position, size, orientation and other variations, should be interpreted for the purpose of understanding objects or patterns as human's intuition does. In this paper, the performance of OBS and Moment Invariant Method is compared with respect to measuring similarity between patterns more intuitively.

2. Relative Similarity Measurement of 2D Patterns Using OBS

The difference between two pieces of information on 2D or 3D objects classifies a group of objects. Most of the 2D or 3D objects can be approximated by polygons of polyhedra to the degree of detail we desire to obtain. The polygons or polyhedra possess geometrical characteristics that may be mapped into another form of data which we call the feature.

OBS is a nonlinear operator that transforms the geometrical information of a pattern (3D, 2D objects) to a norm matrix [1]. This operator is initially presented by the steps obtaining a feature matrix for a three-dimensional object. This operator is also applicable

正 會 員 : 韓國電子通信硏究院·工博
接受日子 : 1998年 7月 30日
最終完了 : 1998年 11月 14日

to obtaining the feature of two-dimensional patterns.

Now let's choose a set of open balls, the open ball is defined in Eq.1 that are all centered at a point, x_0 where a vertex locates. Since a three-dimensional object in the real world can be approximated by the finite number of vertices, there exists a ball that contains the approximated model object inside it.

Given a point x_0 in a set X and a real number $r > 0$, we define a set as an open ball:

$$B(x_0; r) = x \in X | d((x, x_0) < r) \quad (1)$$

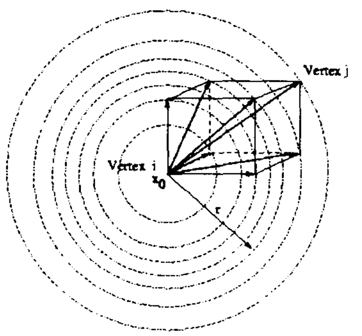

Fig. 1 Open-Ball on an object

First, we measure norms from a chosen vertex to other vertices as described in Fig. 1. The norm in three-dimensional space is the distance between two vertices as defined in Eq. (2). The i th vertex is the center of an open ball as defined below:

$$norm\, s_i = d_{i,j}(vertex_i, vertex_j) \quad (2)$$

where i and j are integers in the range of $[0, N]$ where N is the number of vertices of an object. From a set of the norms obtained by Eq. (2), we selectively choose norms such that the concave of the surface of an object can be distinguished from the convex. Then, we normalize a set of norms for a vertex, such that all norms are within a unit interval $[0, 1]$, as defined in Eq. (3).

$$f(i, j) = \frac{norm(i, j)}{\max_i} \quad (3)$$

where i refers the i th vertex as a center of an open-ball and j refers other vertices of an object. Qualitatively, for a fixed vertex at a center of an open-ball, there are moments that the closure of the open ball meets a set of vertices as the radius of an open ball increases [2,3]. In both two dimensional pattern(image with elevation), and three-dimensional object, OBS can be used to extract a feature for recognition and classification by measuring the degree of similarity. The real interval $[0, 1]$ is uniformly partitioned into a proper number of sub-intervals for each columns (or rows) and count the number of norms that are mapped into each sub-interval as a statistical frequency at each partition. This yields a sequence that has the same number of elements as the number of partitions. The magnitude of each vector is normalized with respect to the sum of the magnitude of each vector, such that the total weights of vector becomes 1.0. The degree of similarity between each patterns is measured by finding the mean of the full connection between each pattern and each of the set of patterns compared as shown in Eq. (4).

$$Similarity = \frac{1}{N}\sum_{i=1}^{N} W_i, \quad W_i = \max < x_i, y_j > \quad (4)$$

where $<\ ,\ >$ denotes the inner product of vectors x_i and y_i, $i = 1, 2, \cdots, N$, $j = 1, 2, \cdots, M$, and M, N are the number of vertices of the patterns. Each of the vertex of a pattern is equally weighted, such that the similarity is obtained by the mean value of the similarities of columns(or rows).

3. Moment Invariant Feature Extraction Method

Moment Invariant refers to a statistical method of feature extraction for classification that has been used in various areas for different applications for decades. The moment invariant is developed by Hu in 1962 and the features for 2-D pattern were presented in [5]. The two-dimensional moments of order $(p+q)$ of an area A with the continuous image intensity function $f(x, y)$ are defined as:

$$m_{p,q} \stackrel{\text{def}}{=} \int\int x^p y^q f(x, y)\,dx\,dy, \ \text{for } p, q = 0, 1, 2, \cdots \quad (5)$$

where x, $y \in A$. The central moments are defined as

$$\mu_{pq} = \int\int (x-\bar{x})^p (y-\bar{y})^q f(x, y)\,dx\,dy \quad (6)$$
$$\text{where } \bar{x} = \frac{m_{10}}{m_{00}} \quad \bar{y} = \frac{m_{01}}{m_{00}}$$

The moment sequence (m_{pq}) in the process is uniquely determined by $f(x, y)$ if $f(x, y)$ is piecewise continuous and has nonzero values only in a finite part of the $f(x, y)$. In other words, (m_{pq}) can uniquely determine $f(x, y)$.

The central moments up to the order $p+q \leq 3$ are calculated by the following formulas:

$$\mu_{00} = m_{00},$$

$$
\begin{aligned}
\mu_{10} &= 0, \\
\mu_{01} &= 0, \\
\mu_{01} &= 0, \\
\mu_{20} &= m_{20} - \bar{x} m_{10}, \\
\mu_{02} &= m_{02} - \bar{y} m_{01}, \\
\mu_{30} &= m_{30} - 3\bar{x} m_{20} + 2\,\bar{x}^2 m_{10}, \\
\mu_{12} &= m_{12} - 2\bar{y} m_{11} - \bar{x} m_{02} + 2\,\bar{y}^2 m_{10} \\
\mu_{21} &= m_{21} - 2\bar{x} m_{11} - \bar{y} m_{20} + 2\,\bar{x}^2 m_{01}, \\
\mu_{03} &= m_{03} - 3\bar{y} m_{02} + 2\,\bar{y}^2 m_{01}
\end{aligned} \tag{7}
$$

The central moments are invariant to translation and can be normalized to be invariant to scaling using the equation below:

$$
\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \tag{8}
$$

$$
\text{where } \gamma = \frac{p+q}{2} + 1, \text{ for } p+q = 2,3,\cdots
$$

The features developed by [5] are shown in the following equations where ϕ_i, $i=1,2,\cdots,7$ are to be invariant to scaling, translation, and rotation.

$$
\begin{aligned}
\phi_1 &= \eta_{02} + \eta_{20} \\
\phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
\phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2 \\
\phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{03} + \eta_{21})^2 \\
\phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&\quad + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{02}^2) - (\eta_{21} + \eta_{03})^2] \\
\phi_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
&\quad + 4\eta_{11}(\eta_{12} + \eta_{03})(\eta_{21} + \eta_{03}) \\
\phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&\quad + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned} \tag{9}
$$

The invariants are second and third order. The invariants from ϕ_1 to ϕ_6 are six absolute orthogonal invariants. ϕ_7 is a skew orthogonal invariant that is useful in distinguishing mirror images.

The degree of difference between patterns is obtained as an l^2 metric distance between the vectors each of which consists of seven elements $\phi_1, \phi_2, \phi_3, \phi_4, \phi_5, \phi_6, \phi_7$ that construct a seventh-dimensional information space. From Least Square Error(LSE) measured, the degree of similarity is measured as the 1's complement of the metric relative difference where 1 is defined as the similarity between the same pattern with invariance on scale, translation, and rotation.

4. Comparison between Moment Invariant Method and Open-Ball Scheme

The property of Moment Invariant method with invariance on scale, shift, and rotation is excellent for a pattern classification purpose [5-7]. However, there exist problems that the parameters ϕ's should be understood with complete understanding its implication. When we use the seven parameters ϕ's for classification purpose, each pattern is denoted by a vector that consists of seven elements. In general, the interpretation of ϕ's is the distance between the vectors that represent patterns.

The distance measured in l^2 metric classifies a group of patterns with the degree of difference. The chosen value can be obtained for different patterns, such that the difference needs to be defined by the signs of the parameters ϕ's. The signs of parameters can be used for obtaining some implication of the characteristics of patterns, for instance the sign of the seventh parameter implies mirror tendency of the compared patterns. Above all, Moment Invariant method may be used for classification in a restricted group of patterns by separating patterns, but it lacks the ability of measuring the degree of similarity between compared patterns.

Compared to Moment Invariant method, OBS possesses several advantages because OBS is developed based on the geometrical structure of patterns. Using OBS, the relative similarity between patterns can be measured, which can hardly be done using Moment Invariants. The interpretation of the relative similarity describes the relationship between patterns as an N-dimensional information space where N is the number of compared patterns. Table 2, 3 shows a case of similarity measurements between the patterns in Fig. 1, 2, 3, 4, 5, 6, 7, 8. The scale numbers indicate the degree of closeness between two shapes. In this experiment, the l^2 metric is used in measuring distance between two patterns.

5. Experimental Results

In order to show that the efficiency and accuracy of Open-Ball Scheme, the patterns in Figures 2 to 15 are used. Comparison is established by showing which algorithm is closer to human's intuitive understanding. The performances of Moment Invariance are tabulated in Tables 2, 5 and the performances of Open-Ball Scheme in Tables 3, 6.

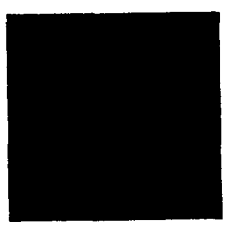

Fig. 2 Pattern 1

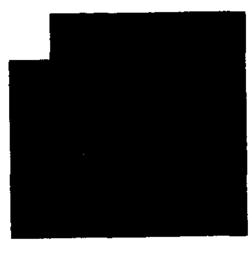

Fig. 3 Pattern 2

Fig. 4 Pattern 3

Fig. 5 Pattern 4

Fig. 6 Pattern 5

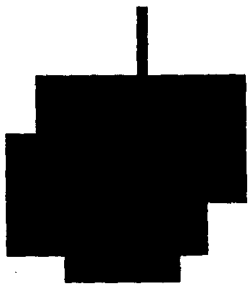

Fig. 7 Pattern 6

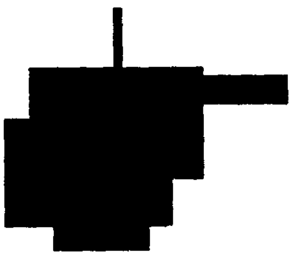

Fig. 8 Pattern 7

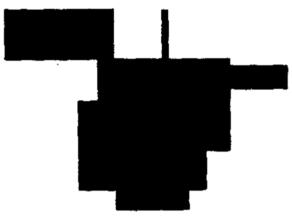

Fig. 9 Pattern 8

In Table 1, seven parameters for each pattern are extracted from Moment Invariant method. Table 2 describes the relative degree of closeness between Fig. 2, 3, 4, 5, 6, 7, 8, 9 as the 1's complements of the l^2 metric distance from the Moment Invariants. Table 3 shows the relative similarities between the chosen eight Figures by mapping the degree of closeness into a point on the [0, 1] real interval using OBS that employed 300 number of partitions in [0, 1].

Table 1 Moment Invariants for Rectangular Patterns.

Pattern	Pat. 1	Pat. 2	Pat. 3	Pat. 4	Pat. 5	Pat. 6	Pat. 7	Pat. 8
ϕ_1	8.15e-04	8.62e-04	9.04e-04	9.36e-04	9.56e-04	9.62e-04	9.77e-04	1.08e-03
ϕ_2	5.24e-08	6.07e-08	6.73e-08	6.83e-08	7.47e-08	7.61e-08	7.19e-08	1.03e-07
ϕ_3	2.81e-13	5.52e-13	8.99e-13	1.49e-12	2.66e-12	2.86e-12	3.45e-12	7.39e-13
ϕ_4	1.53e-12	2.39e-12	4.13e-12	8.98e-12	1.18e-11	1.24e-11	1.82e-11	1.53e-11
ϕ_5	8.35e-25	1.45e-24	6.85e-24	3.15e-23	5.92e-23	6.76e-23	1.44e-22	4.73e-23
ϕ_6	2.79e-16	2.60e-16	8.72e-16	2.14e-15	2.62e-15	2.89e-15	4.47e-15	4.79e-15
ϕ_7	-5.71e-25	-2.33e-24	-4.06e-24	-9.70e-24	-2.93e-23	-3.02e-23	-1.43e-23	2.04e-23

Table 2 l^2 Metric Similarity Measurement Using Moment Invariants.

Sim.	Pat. 1	Pat. 2	Pat. 3	Pat. 4	Pat. 5	Pat. 6	Pat. 7	Pat. 8
Pat. 1	1.0	0.999952	0.999910	0.999878	0.999858	0.999852	0.999837	0.999734
Pat. 2	0.999952	1.0	0.999957	0.999925	0.999905	0.999899	0.999884	0.999781
Pat. 3	0.999910	0.999957	1.0	0.999967	0.999947	0.999941	0.999926	0.999823
Pat. 4	0.999878	0.999925	0.999967	1.0	0.999979	0.999973	0.999958	0.999855
Pat. 5	0.999858	0.999905	0.999947	0.999979	1.0	0.999993	0.999978	0.997655
Pat. 6	0.999852	0.999899	0.999941	0.999973	0.999993	1.0	0.999984	0.999988
Pat. 7	0.999837	0.999884	0.999926	0.999958	0.999978	0.999984	1.0	0.999896
Pat. 8	0.999734	0.999781	0.999923	0.999855	0.997655	0.999987	0.999896	1.0

Table 3 Classification Between Rectangular Simple Models Using OBS.

Sim.	Pat. 1	Pat. 2	Pat. 3	Pat. 4	Pat. 5	Pat. 6	Pat. 7	Pat. 8
Pat. 1	1.0	0.4364	0.4364	0.3901	0.3443	0.3140	0.2844	0.2637
Pat. 2	0.4364	1.0	0.5067	0.4554	0.4003	0.3302	0.3290	0.3009
Pat. 3	0.4364	0.5064	1.0	0.4734	0.3857	0.3318	0.3219	0.3031
Pat. 4	0.3901	0.4554	0.4734	1.0	0.4197	0.3518	0.3419	0.3022
Pat. 5	0.3443	0.4003	0.3857	0.4197	1.0	0.3117	0.3232	0.3040
Pat. 6	0.3140	0.3302	0.3318	0.3518	0.3117	1.0	0.3370	0.3147
Pat. 7	0.2844	0.3290	0.3219	0.3419	0.3232	0.3370	1.0	0.3255
Pat. 8	0.2637	0.3009	0.3031	0.3022	0.3040	0.3147	0.3255	1.0

Figure 2 is a simple rectangle and Figures 3, 4, 5, 6, 7, 8, 9 vary in order their shapes as the index increases, such that the adjacent patterns have higher similarity than the other patterns in both Table 2 and 3. For instance, Figure 3 is more similar to Figure 2, 4 than to Figure 8 and 9 in both OBS and Moment Invariant Method. In general, both Moment Invariant Method and Open-Ball Scheme show that the patterns adjacent to a chosen pattern possess higher relative similarities than the others in Table 2 and Table 3.

However, the method of OBS shows a better performance than Moment Invariant Method by being more similar to the human's understanding.. Figure 4 is closer to the Figure 2 than Figures 6, 7, and 8 based on human's intuitive understanding. This implies that Moment Invariant method may not perform as human's intuition works. Figure 5 also has closer relation to Figures 6, 7, and 8 than Figures 3 and 4 by Moment Invariant method, while OBS shows that Figure 5 is closer to Figure 3 and 4 than the other. Figure 6 has a similar tendency being closer to Figures 3, 4 and 5 in OBS. Figures 7, 8 and are classified reasonably in both OBS and Moment Invariant Method, but Figure 9 is not classified well by Moment Invariants compared to OBS as shown in Tables 2 and 3.

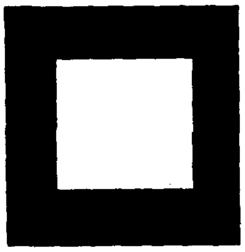

Fig. 10 Test 1

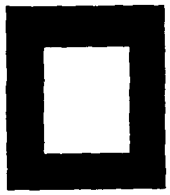

Fig. 11 Test 2

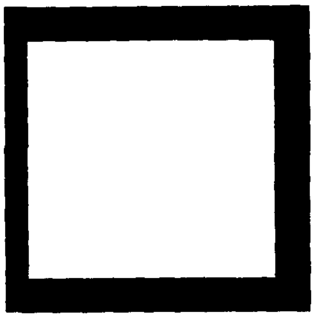

Fig. 12 Test 3

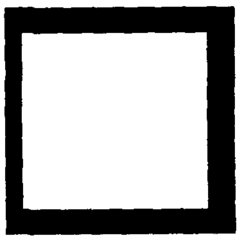

Fig. 13 Test 4

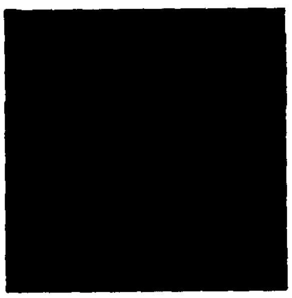

Fig. 14 Test 5

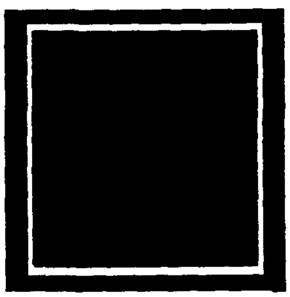

Fig. 15 Test 6

The similarity measurements between Figures 10, 11, 12, 13, 14 and 15 are also evaluated with respect to the human's intuition. Figures 12 and 13 are the same pattern with different scale. In general, Figures show higher similarity to the adjacent patterns that vary small amount in shape then other not adjacent in both Moment Invariant Method and Open-Ball Scheme. The difference between Moment Invariants and Open-Ball Scheme appears in the relation between Figure 14 and 15.

Table 4 describes the seven parameters from Moment Invariant for Figures 10 to 15. The metric distance between the feature vectors each of which consists of seven number of parameters in Table 4 is shown in Table 5.

As a comparison to the Table 5, the relative distance by Open-Ball Scheme between Figures 10 to 15 is shown in Table 6 with 20 partitions in [0, 1].

In OBS, the Figure 15 shows a closer relation to Figure 14 than to Figures 10, 11, 12, 13 but Moment Invariant Method shows that Figure 14 is closer to Figure 13 than Figure 15, which is not the way human intuition works. This also implies that OBS performs better than Moment Invariant Method for measuring the relative similarities between 2-D patterns.

Table 4 Moment Invariants for Rectangular Patterns.

ϕ	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6
ϕ_1	8.5992e-04	7.6683e-04	8.6080e-04	8.6080e-04	1.144e-03	1.5126e-03
ϕ_2	6.1046e-08	4.7891e-08	6.3124e-08	6.3124e-08	1.0068e-07	1.6261e-07
ϕ_3	9.6648e-14	2.3362e-14	1.0485e-13	1.0485e-13	4.9749e-12	3.8620e-11
ϕ_4	3.0163e-13	8.0516e-14	3.1086e-13	3.1086e-13	2.9954e-11	2.2570e-10
ϕ_5	-9.5948e-27	1.6352e-27	-1.7432e-26	-1.7432e-26	3.5448e-22	1.9486e-20
ϕ_6	-2.4279e-17	4.8635e-18	-3.4123e-17	-3.4123e-17	9.1441e-15	8.3239e-14
ϕ_7	5.0597e-26	3.0855e-27	5.3344e-26	5.3344e-26	-8.9749e-23	-8.0369e-21

Table 5 l^2 Metric Similarity Measurement Using Moment Invariants.

Sim.	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6
Test 1	1.0	0.9999069	0.9999991	0.9999991	0.9997159	0.9993473
Test 2	0.9999069	1.0	0.9999060	0.9999060	0.9996228	0.9992542
Test 3	0.9999991	0.9999060	1.0	1.0	0.9997167	0.9993481
Test 4	0.9999991	0.9999060	1.0	1.0	0.9997167	0.9993481
Test 5	0.9997159	0.9996228	0.9997167	0.9997167	1.0	0.9996313
Test 8	0.9993473	0.9992542	0.9993481	0.9993481	0.9996313	1.0

Table 6 Similarity Measurements Between Rectangular Patterns Using OBS.

Pattern	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6
Test 1	1.0	0.7964	0.7155	0.7155	0.7359	0.6754
Test 2	0.7964	1.0	0.7335	0.7335	0.7100	0.6917
Test 3	0.7155	0.7335	1.0	1.0	0.7585	0.7059
Test 4	0.7155	0.7335	1.0	1.0	0.7585	0.7059
Test 5	0.7359	0.7100	0.7585	0.7585	1.0	0.9161
Test 6	0.6754	0.6917	0.7059	0.7059	0.9161	1.0

6. Conclusion

In this paper, the performance of OBS is presented with comparison to one of the effective feature extraction methods, Moment Invariant Method. OBS shows better performance than Moment Invariant Method by not only classifying 2D patterns with invariance to rotation, scale, and shift but also interpreting more closely to the way human intuition understands patterns.

The experimental results show that the relative similarity between 2D patterns by mapping the measurement onto the real interval [0. 1]. The implication of experiments may be due to the difference between the properties of two feature extraction methods, OBS depends on the geometrical structure of patterns and Moment Invariant method is a statistical feature extraction method.

References

[1] S. S. Kim, "3D Object Recognition Via the Open-Ball Scheme Using the Modified Domain Deformation Theory and Wavelets", Ph.D. dissertation, UCF, Orlando, FL, 1997.

[2] S. S. Kim, T. Kasparis, and G. A. Schiavone, "Three-dimensional object recognition using wavelet de-noising", SPIE AeroSense, 1996.

[3] S. S. Kim, T. Kasparis, G. A. Schiavone, and C. R. Madhudram, "A similarity measure for non-uniformly sampled multi-resolution terrain data using open-ball operator", The 30th IEEE Conf. on Signals, Systems and Computers, Asilomar, Nov. 1996.

[4] Rafael C. Gonzalets, Richard E. Wood, Digital Image Processing, Addisson- Wesley, 1993.

[5] M. K. Hu, "Visual Pattern Recognition by Moment Invariants", IRE Tansactions on Information Theory, 179-187, February 1962.

[6] T. H. Reiss, "The Revised Fundamental Theorem of Moment Invariants", IEEE Tans. on PAMI Vol. 13, NO 8, 830-834, August 1991.

[7] F. A. Sadjadi, E. L. Hall, "Three-Dimensional Moment Invariants", IEEE Trans. on PAMI Vol. PAMI-2, NO. 2, March 1980.

[8] Simon X. Liao, Miroslaw Pawlak, "On Image Analysis by Moments", IEEE Trans. on PAMI Vol. 18, NO. 3, March 1996.

저 자 소 개

김 성 수(金 聖 洙)

1959년 5월 17일생. 1983년 충북대학교 전기공학과 졸업. 1989년 알칸소주립대 전기공학과 졸업(석사). 1997년 중앙플로리다 주립대학 졸업(공박). 현재 전자통신연구원 Post. Doc.