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Fourier Descriptor features for Shape Deformation Classification using Random Kitchen Sink

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ABSTRACT

This paper deals with the Fourier descriptor features for shape deformation classification using Random Kitchen Sink algorithm accessed through GURLS library. Shape recognition is an important method used in all industrial environments which are mostly concerned with robots. It is a highly essential task to make the robot understand the shape of an object. The object may have many deformed shapes and so it is necessary to train the classifier accordingly. Recognition methods based on polar coordinates and probabilistic models are already developed, but its accuracy for finding the deformed shape of the object is low. In this context, Random Kitchen Sink algorithm is used and the classification is done through GURLS in which, regularized least square method is used, which leads to better shape recognition.

KEY WORDS: Random Kitchen Sink, shape recognition, shape deformation, GURLS, polar coordinates, Fourier Descriptor.

1. INTRODUCTION

Shape deformation is a useful technique in the field of computer vision and robotics. The usages of robots in the industrial and household environments are rapidly increasing. Since these robots are working around with objects, it is necessary for the robots to learn and understand the object shapes and its deformations. The challenging task is to make the robots to understand the shape of the objects and its deformation. The algorithms based on probabilistic models and polar coordinates have been developed for this challenging task. Shape puzzle model is relatively similar in shape. This is used to determine the robustness of the system. Shape descriptors are classified into two categories namely, region based and contour based. In region based model, shape descriptors of every pixel is taken for shape deformation whereas, in contour based category only boundary value information is taken from the shape deformation. Fourier descriptor is generally contour based, which captures low frequency terms for global shapes and high frequency terms for finer features of the shape. Most of the information resides on low frequency and finer boundary values are lost in high frequency region. In Fourier descriptor rotation, translation and scaling make difference in descriptors.

Wavelet descriptor has an advantage over Fourier descriptor since, wavelets helps to localize frequency and spatial domain for a specific artifact. For higher dimensional feature matching, wavelet descriptor is impractical [8]. Whereas, Fourier descriptor can be easily normalized and it is the most common technique used for shape recognition and shape description. Fourier descriptor has been used in various fields like computer vision, human figure identification, shape classification and character recognition. It includes central distance, complex coordinates and cumulative angles. Polar coordinates are used in the experimental model because it produces more accurate results than complex coordinates. Procrustean models, geometric features, probability density functions and generative models are some of the probabilistic models used for shape recognition.

In this paper, methodology is proposed based on Fourier descriptor features for shape deformation classification using Random Kitchen Sink accessed through GURLS library. Shapes are made using cardboard and the images of each shapes are captured using a camera. The coordinates of the shapes are determined using GNU Image Manipulating Program (GIMP) software. The Euclidean distance between the coordinates is computed as a feature to recognize the shapes of the object. To make the deformation better, Fourier Descriptors are used as features since its magnitude never changes. The features of the deformed shapes are subjected to Random Kitchen Sink algorithm and classified using Regularized Least Square classifier.

Random Kitchen Sink: Random Kitchen Sink (RKS) works on the principle of Bochner's theorem. RBF kernel function is given by

$$k(x,y)=\langle\phi(x),\phi(y)\rangle=e^{-\sigma\|x-y\|_c^2}=e^{-\sigma(x-y)^T(x-y)} \qquad (1)$$

$$e^{-\sigma(x-y)^T(x-y)}=e^{-\sigma z^T z}=f(z) \qquad (2)$$

According to Bochner's theorem, the Fourier Transform of this function $f(z)$ is given by

$$F(\Omega)=\int f(z)e^{-jz^T\Omega}dz \qquad (3)$$

Since $f(z)$ is real and symmetric, $F(\Omega)$ is again real and symmetric and is a multivariate Gaussian function in equation 2. The point to be noted here is that any Gaussian function after scaling can be viewed as a probability distribution function. Here $f(z)$ is Gaussian, so $F(\Omega)$ is also a Gaussian function but it is a multivariate

Gaussian probability distribution function. Random kitchen sink is based on the fact that inverse Fourier Transform of RBF (radial basis function) kernel can be interpreted as expectation of a random variable. So the inverse Fourier Transform of $F(\Omega)$ must be equal to $\langle \phi(x), \phi(y) \rangle$ and it is given by $\int F(\Omega) e^{jz^T\Omega} d\Omega$. Here, the distribution is a multivariate Gaussian distribution, and let us assume that the variable involved here is independent and hence the multivariate vector Ω_i is also generated independently. The tuple size of Ω_i is same as z. k variables are chosen from the distribution.

$$E(e^{jz^T\Omega}) \approx \frac{1}{k}\sum_{i=1}^{k} e^{j\Omega_i^T z} = \frac{1}{k}\sum_{i=1}^{k} e^{j\Omega_i^T (x-y)} = k(z) \tag{4}$$

$$= \frac{1}{k}\sum_{i=1}^{k} e^{j\Omega_i^T x} e^{-j\Omega_i^T y} \tag{5}$$

Now, $k(x,y) = \langle \phi(x), \phi(y) \rangle$

$$= \frac{1}{k} sum\left(\begin{bmatrix} e^{j(x-y)^T\Omega_1} \\ e^{j(x-y)^T\Omega_2} \\ \vdots \\ \vdots \\ e^{j(x-y)^T\Omega_k} \end{bmatrix}\right) \quad = \frac{1}{k}\left\langle \begin{bmatrix} e^{jx^T\Omega_1} \\ e^{jx^T\Omega_2} \\ \vdots \\ \vdots \\ e^{jx^T\Omega_k} \end{bmatrix}, \begin{bmatrix} e^{jy^T\Omega_1} \\ e^{jy^T\Omega_2} \\ \vdots \\ \vdots \\ e^{jy^T\Omega_k} \end{bmatrix} \right\rangle \quad = \left\langle \begin{bmatrix} \frac{1}{\sqrt{k}} e^{jx^T\Omega_1} \\ \frac{1}{\sqrt{k}} e^{jx^T\Omega_2} \\ \vdots \\ \vdots \\ \frac{1}{\sqrt{k}} e^{jx^T\Omega_k} \end{bmatrix}, \begin{bmatrix} \frac{1}{\sqrt{k}} e^{jy^T\Omega_1} \\ \frac{1}{\sqrt{k}} e^{jy^T\Omega_2} \\ \vdots \\ \vdots \\ \frac{1}{\sqrt{k}} e^{jy^T\Omega_k} \end{bmatrix} \right\rangle$$

Here,

$$\phi(x) = \left\langle \begin{bmatrix} \frac{1}{\sqrt{k}} e^{jx^T\Omega_1} \\ \frac{1}{\sqrt{k}} e^{jx^T\Omega_2} \\ \vdots \\ \vdots \\ \frac{1}{\sqrt{k}} e^{jx^T\Omega_k} \end{bmatrix} \right\rangle \text{ and } \phi(y) = \left\langle \begin{bmatrix} \frac{1}{\sqrt{k}} e^{jy^T\Omega_1} \\ \frac{1}{\sqrt{k}} e^{jy^T\Omega_2} \\ \vdots \\ \vdots \\ \frac{1}{\sqrt{k}} e^{jy^T\Omega_k} \end{bmatrix} \right\rangle$$

This basically explains that n-tuple x is mapped to k-tuples of complex number, here k is greater than n. Now to avoid complex numbers, each value is converted into its cosine and sine, further appending it to form $2k$-tuples. This is given below,

$$\phi(x) = \frac{1}{\sqrt{k}} \begin{bmatrix} Cos(x^T\Omega_1) \\ Cos(x^T\Omega_2) \\ \vdots \\ Cos(x^T\Omega_k) \\ Sin(x^T\Omega_1) \\ Sin(x^T\Omega_2) \\ \vdots \\ Sin(x^T\Omega_k) \end{bmatrix}$$

This is an explicit mapping corresponding to Gaussian kernel.

2. PROPOSED SYSTEM

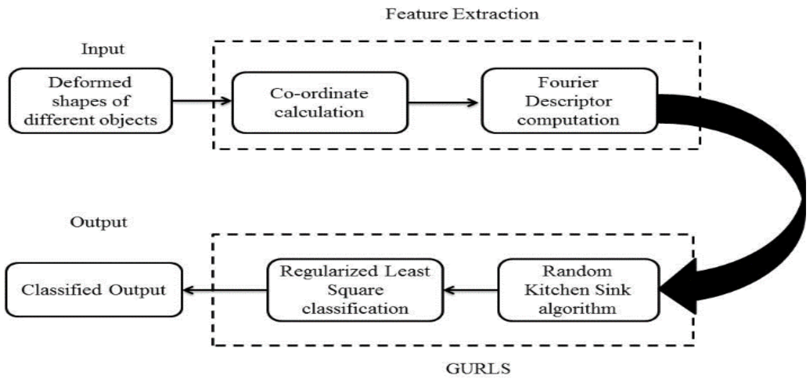

Fig.1.Flow diagram of the proposed system

The proposed system aims to explore the Fourier descriptors for shape deformation classification using Random Kitchen Sink (RKS) and accessed through Regularised Least square (RLS). The different stages of the proposed methodology is shown in fig 1.The proposed system makes use of Random Kitchen Sink (RKS) algorithm for classifying the deformed shapes. Random Kitchen Sink (RKS) classification is accessed via GURLS. Initially the shapes off different objects are made from cardboard. The shapes of the objects and its deformations are captured using a camera. Deformations of the objects are formed by subjecting the object to rotation and scaling. After capturing the images, coordinates of the objects are calculated using GNU Image Manipulating Program (GIMP) software. This paper deals with the contour based method, where only few of the points from the boundary are taken into account. The center of the objects are deliberated from the boundary points, using the formula

$$\left(\frac{x_1 + x_2 + ... + x_n}{n}, \frac{y_1 + y_2 + ... + y_n}{n} \right)$$

Where $(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)$ are the points from the boundary of the objects. Polar coordinate of each points from the origin of the objects are computed using the formula, $d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$ (7) where the d is the distance between the points (x_1, y_1) and (x_2, y_2). Then, the Fourier descriptor of the objects is computed using the distance, this is due to the fact that the magnitude of the Fourier descriptor will never change.

Table.1.Confusion matrix obtained by the proposed method

Classes	1	2	3	4	5	6	7	8	9	10
1	4	0	0	0	0	0	0	0	0	0
2	0	3	0	0	0	0	0	0	0	1
3	0	0	4	0	0	0	0	0	0	0
4	0	0	0	4	0	0	0	0	0	0
5	0	0	0	0	3	1	0	0	0	0
6	0	0	0	2	0	2	0	0	0	0
7	0	0	0	0	0	0	4	0	0	0
8	0	0	0	0	0	0	0	4	0	0
9	0	0	0	0	0	0	0	0	4	0
10	0	0	0	0	1	0	0	0	0	3

GIMP: GIMP stands for the acronym GNU Image Manipulating Program. It is a freely distributed program for task such as photo retouching, image composition, image authoring etc. It is written and developed under X_{11} on UNIX platform. In this context, the GIMP software is used to determine the coordinates for the boundary of an object, which is further used to calculate the centroid of the objects.

GURLS: GURLS stands for the acronym Grand Unified Regularized Least Square. It works on the Regularized Least Square (RLS) algorithm, which is one of the simplest algorithms for Supervised Learning. RLS has connection estimation with Gaussian processes and discriminant analysis. This method is used as an alternative for learning methods like Support Vector Machine (SVM). It is designed especially for solving multi-category classification problem. Here multiple classes are classified using Random Kitchen Sink algorithm and the classified outputs are accessed using GURLS.

Table.2.Classification Accuracy of the proposed method

Shapes	Accuracy (in %)
Moon	100%
Heart	75%
Arrow	100%
Polygon	100%
Hexagon	75%
Leaf	50%
Fish	100%
Butterfly	100%
Thunder	100%
Flower	75%

3. RESULTS AND DISCUSSIONS

The proposed method of shape deformation classification based on Fourier descriptors is experimented on ten different shapes namely moon, heart, arrow, polygon, hexagon, leaf, fish, butterfly, thunder and flower. These ten different shapes act as ten classes, which are shown in fig 2. Each shape is subjected to ten different deformations such as rotation to various degrees such as, $45^{\circ}, 60^{\circ}, 90^{\circ}, 120^{\circ}$ etc., and by zooming the shape in and out. The deformation of a single shape is shown in fig 3. The Fourier descriptor features of each deformed shape are computed as explained in the proposed methodology available in section III. The descriptor feature size of each deformed shape is 32×1. The classifications are computed using Random Kitchen Sink and are accessed through GURLS library. 60% and 40% of the data is given for training and testing respectively for classification. Out of ten deformations available, six deformations and four deformations are taken for training and testing respectively. Class label is given for each class to indicate the class belonging to the particular deformed shape. The classified and misclassified output of the training set is given in confusion matrix which is shown in Table 2. The diagonal elements in the confusion matrix correspond to the number of correctly classified data and the number of misclassified data is represented as the non-diagonal elements. Classification accuracy of the propose system is shown in the Table 1. The classes moon, arrow, polygon, fish, butterfly, thunder contribute a maximum accuracy and the classes heart, hexagon, leaf offers less accuracy due to the misclassification of the classes The overall accuracy obtained for the proposed methodology of shape recognition is 87.5%.

In the existing method, two models are executed one using the complex coordinate and other using polar coordinate. The solutions obtained using the complex coordinate is only 30% and the one which is obtained using the polar coordinate is 80%. The classification of shape recognition using the proposed method yields an accuracy of 87.5%.

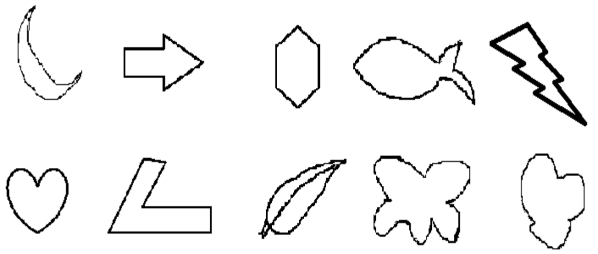

Figure.2.Different shapes used in the proposed system

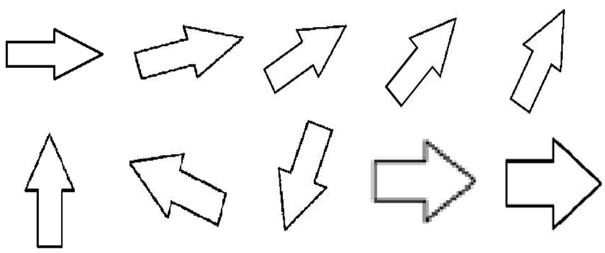

Figure.3.Deformation of a sample shape

4. CONCLUSION

We have presented an approach to classify different 2D shape deformation which is highly essential in the field of robotics. In this work, ten different shapes are formed and the deformations of those shapes are considered for the classification. By using RKS algorithm and regularized least square classifier it is observed that better classification results are obtained. This method can also be extended for the 3D shape deformation, as a future work.

REFERENCES

Besl, Paul J, and Ramesh C Jain, Three-dimensional object recognition, in Proc. ACM Computing Surveys (CSUR) 17, 1, 1985, 75-145.

Chin, Roland T, and Charles R Dyer, Model-based recognition in robot vision, in Proc. ACM Computing Surveys (CSUR) 18, 1, 1986, 67-108.

Diaz De Leon R, and Luis Enrique Sucar, Human silhouette recognition with Fourier descriptors, in Proc. 15th International Conference, 3, 2000.

Duda, Richard O, Peter E Hart, Pattern classification, in Proc. John Wiley and Sons, 2012.

Gonzalez, Rafael C, Digital image processing, 2nd., in Proc. SL: Prentice Hall 2, 2002.

Janse van Rensburg F.J, Treurnicht J, The Use of Fourier Descriptors for Object Recognition in Robotic Assembly, in Proc. 5th CIRP International Seminar, 2006.

Kauppinen, Hannu, An experimental comparison of autoregressive and Fourier-based descriptors in 2D shape classification, in Proc. Pattern Analysis and Machine Intelligence, 17.2, 1995, 201-207.

Persoon, Eric, and King-Sun Fu, Shape discrimination using Fourier descriptors, in Proc. Systems, Man and Cybernetics, 7.3, 1977, 170-179.

Rahimi, Ali, and Benjamin Recht, Weighted sums of random kitchen sinks: Replacing minimization with randomization in learning, in Proc. Advances in neural information processing systems, 2009.

Rauber, Thomas W, Two-dimensional shape description, in Proc. GR UNINOVA-RT, 10-94, 1994.

Tacchetti, Andrea, GURLS: a toolbox for large scale multiclass learning, in Proc. NIPS 2011 workshop on parallel and large-scale machine learning, 2011.

Taubin, Gabriel, and David B Cooper, Object recognition based on moment (or algebraic) invariants, in Proc. IBM TJ Watson Research Center, 1991.

Taubin, Gabriel, Object recognition based on moment (or algebraic) invariants, in Proc. Geometric Invariance in Computer Vision, 1992, 375-397.

Teh C.H, and Roland T Chin, On image analysis by the methods of moments, in Proc. Pattern Analysis and Machine Intelligence, IEEE Transactions, 10.4, 1988, 496-513.

Wang, Yanzhen, 2D shape deformation based on rigid square matching, in Proc. Computer Animation and Virtual Worlds 19, 3-4, 2008, 411-420.

Williams, Christopher KI, and Carl Edward Rasmussen, Gaussian processes for machine learning, in Proc. the MIT Press, 2.3, 2006, 4.

Yang, Hee Soo, Recognition of 2D object contours using starting-point-independent wavelet coefficient matching, in Proc. Journal of visual communication and image representation, 9.2, 1998, 171-181.