Automatic Recognition of Rodent Species based on Mathematical Morphological Characterization of Skull

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Abstract— Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. Digital image processing technique applied to extract morphological features of skull image taken from optical camera. Based on the prominent nine extracted morphological features of rodent species, the closed form univariate two-factor analysis is derived. These two factor analysis is used for real time auto-recognition uniqueness of rodent species such as Meriones unguiculatus, Microtus brandti and Rattus norvegicus. The same two-factor auto-recognition analysis is used over x-ray image of rodent's skull as well as other rodent species like squirrel. The considered morphological features are short axis(X1), perimeter(X2), eccentricity(X3), sphericity(X4), bump area(X5), paraxial area of enclosing rectangle(X6), hu1(X7), hu2(X8), hu3(X9).

IndexTerms— Morphological image processing , Hu-moments, Rodent species.

I. INTRODUCTION

Morphology of skull is important in rodent identification. Exploiting the morphological characteristics of rodent skull specimen sufficiently can help to identify rodent automatically by computer. Morphology commonly denotes a branch of biology that deals with the from and structure of animals and plants. Mathematical morphology act as tool for extracting image components (feature) that useful in the representation and description of region shape such as boundaries, skeletons and the convex hull. In this morphological features pertaining to skull has been taken for auto-recognition of rodent species. In this a closed form automatic classification method proposed for the recognition of rodent species. This method is based on morphological segmentation parameters. Feature extraction process is applied to binary image of rodent skull. There are numerous 22 possible morphological features can be extracted. it was experimentally found based on monto-carlo simulation that only nine features considered to be prominent. The closed form weighted relation over prominent nine features is derived to distinguish the rodent species. In this, experiment carried out on collected test vectors in the form of binary images to ascertain the effectiveness of weighted relation.
Mathematical Simulation also have been carried out for 500 such each respective three rodent to tune the functions and make accuracy of the result. is 100% for auto-recognition.

Manuscript received on April , 2014
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In next Section II describes the features taken for auto-recognition, Section III describes about closed form approach weighted function and Section IV there will be elaborate result and discussion with statistical inference and finally followed by concluding remarks and future scope of the research.

II. MORPHOLOGICAL FEATURES FOR RODENT SKULLS

Mathematical morphology has been widely used in biological research and show a great emphasis for auto-recognition. There are nine morphology parameters taken for consideration, which differ among the three rodent species. In contrast, the other remaining morphological parameters only show difference in part of species, and can't be used alone, however, with the adding of new species in classification, those parameters will play its important role probably, simultaneously, more new morphology parameters may be needed to help the accurate judgment. These nine parameters are *Short axis* as describes the average length of minor axis of elliptical contour of the skull. In this the dominant elliptical contour of skull is required to be taken into consideration. *Perimeter* The perimeter is defined as the total pixels that constitutes the edge of the object. Perimeter can help us to locate the object in space and provide information about the shape of the object. Perimeters can be found by counting the number of '1' pixels that have '0' pixels as neighbors. Perimeter can also be found by applying an edge detector to the object, followed by counting the '1' pixels. The two methods as mentioned only give an estimate of the actual perimeter. An improved estimate can be found by multiplying the results from either of the two methods by $\pi/4$. *Eccentricity* The eccentricity of an object can be defined as the eccentricity of the ellipse representing the unit-standard-deviation contour of its points. If we view an object image as a set of points in two-dimensional Cartesian space, then the parameters of the unit-standard-deviation ellipse are easily computed from the covariance matrix of the points. The eccentricity of an ellipse is the ratio of the distance between the foci of the ellipse and its major axis length. The eccentricity is always between zero and one. (Zero and one are degenerate cases; an ellipse whose eccentricity is zero is actually a circle, while an ellipse whose eccentricity is one is a line segment). *Sphericity* it measures the degree to which a particle approaches a spherical shape. It was defined by Wadell (1932) as the ratio between the diameter of a sphere with the same volume as the particle and the diameter of the circumscribed sphere. The sphericity of a particle is usually determined by measuring the three linear

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dimensions of the particle (longest (L), intermediate (I) and shortest (S) diameters) [1]. Sphericity is a measure of how spherical (round) an object is. As such, it is a specific example of a compactness measure of a shape. Defined by Wadell in 1935,[1] the sphericity (Ψ) , of a particle is the ratio of the surface area of a sphere (with the same volume as the given particle) to the surface area of the particle. *Bump Area* it measures the area of projected part of skull. *Paraxial Area enclosing rectangle* The Paraxial Area enclosing rectangle of an object is the smallest rectangle that totally encloses the object. The extent of an object can be defined as the proportion of the pixels within the minimum bounding rectangle of the object that are also in the object. It can be computed as the object area divided by the area of the Paraxial Area enclosing rectangle. *Hu-Moments* Moment invariants have been widely applied to image pattern recognition in a variety of applications due to its invariant features on image translation, scaling and rotation. The moments are strictly invariant for the continuous function.

Moments and the related invariants have been extensively analyzed to characterize the patterns in images in a variety of applications. Moment invariants are firstly introduced by Hu. In[2], Hu derived six absolute orthogonal invariants and one skew orthogonal invariant based upon algebraic invariants, which are not only independent of position, size and orientation but also independent of parallel projection. Moment invariants have been extensively applied to image pattern recognition[3], image registration[4] and image reconstruction. Two-dimensional (p+q)th order moment are defined as follows

$$m_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} x^p y^q f(x,y)\,dxdy \qquad \textbf{p,q = 0,1,2......}$$

If the image function f(x,y) is a piecewise continuous bounded function, the moments of all orders exist and the moment sequence { m_{pq} } is uniquely determined by f(x,y) and corresponding, f(x,y) is also uniquely determined by moment sequence { m_{pq} }. The invariant features can be achieved using central moments, which are defined as follows

$$\mu_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} (x-\bar{x})^p (y-\bar{y})^q f(x,y)\,dxdy$$

The pixel point $(\bar{x},\bar{y})$ are the centroid of the image f(x,y). The centroid moments μ_{pq} computed using the centroid of the image. Therefore the central moments are invariants to image translation. Scale invariance can be obtained by normalization. The normalized central moments are define as follows

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}, \gamma = (p+q+2)/2, p+q = 2,3..........$$

Three required Hu-moments are expressed as follows. These three Hu-moments are considered in paper for rodent auto-recognition.

$$\phi_1 = \eta_{20} + \eta_{02}, \quad \phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^{\ 2}$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \mu_{03})^2$$

III. AUTO-RECOGNITION CANONICAL FUNCTION

The canonical standard closed function are defined based nine weighted features of respective three rodent species skull image. These nine morphological features are computed. The considered nine features are short axis(X1), perimeter(X2), eccentricity(X3), sphericity (X4), bump area(X5), paraxial area of enclosing rectangle(X6) and three Hu moments hu1(X7), hu2(X8), hu3(X9). These functions are

Y1 = 8.014X1 - 3.585X2 + 9.682X3 - 2.504X4 + 7.823X5 - 10.948X6 - 0.896X7 + 12.471X8 - 0.781X9;

Y2 = 2.593X1 + 0.242X2 + 6.323X3 + 0.509X4 - 1.219X5 - 2.898X6 - 4.226X7 + 7.674X8 + 0.785X9

IV. RESULTS AND DISCUSSION

As all extracted morphology parameters were significant, stepwise discriminatory method was used to get very marked morphology parameter, and two standardized canonical discriminate functions were found with nine morphology parameters. The experiment result was carried out with skull image of Meriones. The image taken of 256 X 265 size. The gray level image has been taken and first converted to binary level images. The image taken by optical camera from top projection of skull. As Fig 1 shows the gray level image and Fig 2 shows the binary level converted image.

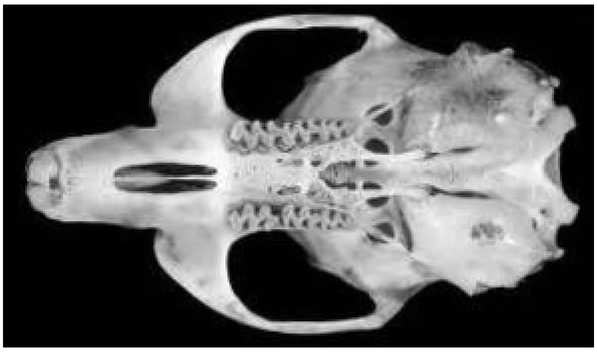

Fig 1: Meriones Skull

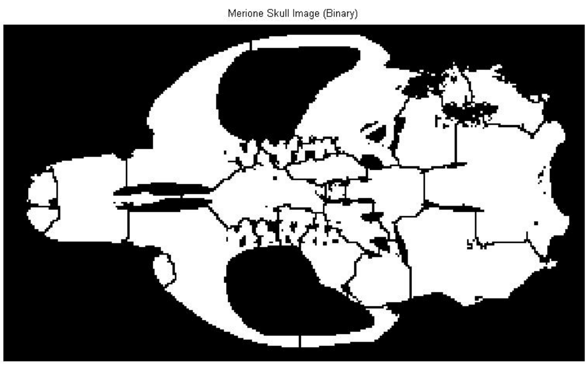

Fig:2 Binary images

The all the required features mean values are found to be Short-Axis (X1)=18.5349, Perimeter (X2)=105.0638, Eccentricity (X3)=0.4653, Sphericity (X4)=0.5114, Bump Area (X5)=424.6863,Paraxial-Area(X6)=606.2571, Hu-Moments1(X7)=1.2968, Hu-Moments2(X8)=3.5762 and Hu-Moments3(X9)=6.8825. The statistical mean value taken over 100 test vectors. The test vectors are based on image sample taken from standard image data base available across over web and also some test vector generated by

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knowing the variance of the extracted feature. The test run made over monte-carlo simulation to get unbiased estimate. With these 100 vectors and computing the optimally weighted cannonical functions Y1 and Y2. The plot shows in Fig 3 the Y2 Vs Y1 for 100 test vectors. The centroid value of this gives the recognition of Meroines.

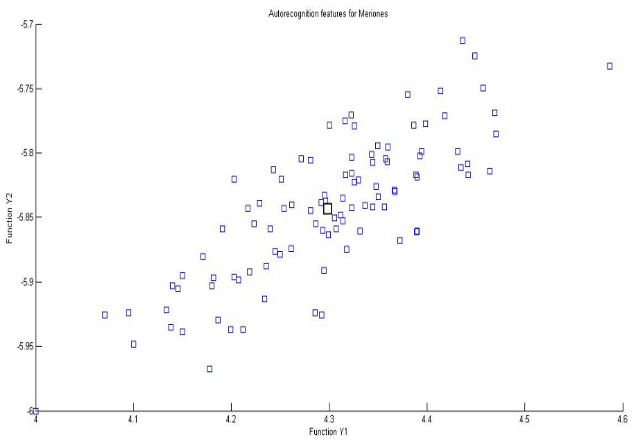

Fig 3: Cannonical function

The variance estimated based normal Gaussian fit model for all nine features are over 100 test vectors,

Features	Variances(Meriones)
Short-Axis	0.698
Perimeter	4.289
Eccentricity	0.014
Sphericity	0.09
BumpArea	27.461
Paraxial-Area	41.662
Hu-Moments1	0.014
Hu-Moments2	0.067
Hu-Moments3	0.092

The same algorithm is also verified across variation rotation effect over the image. The same algorithm applied over rotated image taken from data base as shown in figure 4.

Fig:4 Merioness skull (rotated image)

The same cannonical function is applied for other rodent species like Microtus and Rattus. The image taken from optical camera. However the same cannonical functions Y1 and Y2 is also extended to work over the skull images taken by X-ray. The introduction of X-ray based auto recognition make the projected algorithm to work on real time. The results shown in Fig 5 for the identification three rodent species like Meriones, Microtus and Rattus.

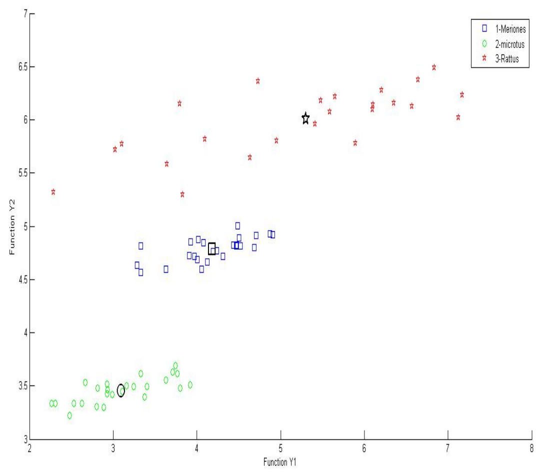

Fig:5 Other rodent species

V. CONCLUSION

The mentioned algorithm is the optimal form for auto recognition for rodent species specially taken meriones, rattus. But the same concept can be enhanced and optimized with more morphological features for auto recognition of other rodent species like squirrel. This can also be enhanced to make the auto-recognition of skull image should be sensor independent like whether the image is of optical camera or X-ray etc..

VI. ACKNOWLEDGMENT

The author like to thank Prof K.Indira for her guidance and encouragement to do novel research work and get the optimal result. The author thanks MSRIT for having given an opportunity to carry out the work uninterruptly.

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