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MATHEMATICAL BASED APPROACH FOR OBJECT CLASSIFICATION

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Abstract: The goal of this study is to build a system that detects and classifies the bike objects amidst background clutter and mild occlusion. This study addresses the issues to classify objects of real world images containing side views of the bike with cluttered background with that of non-bike images with natural scenes**.** The threshold technique with background subtraction is used to segment the background region to extract the object of interest. The background segmented image with region of interest is divided into equal sized blocks of sub-images. The spectral texture features are extracted from each sub block. The features of the objects are fed to the back-propagation neural classifier. Thus the performance of the neural classifier is compared with various categories of block size. Quantitative evaluation shows improved results. A critical evaluation of present approach under the proposed standards is presented.

Keywords: Object classifier, back ground segmentation, spectral features, and back propagation.

INTRODUCTION

Object detection and classification are necessary components in an artificially intelligent autonomous system. Especially, object classification plays a major role in applications such as security system, traffic surveillance systems, etc. It is expected that these artificially intelligent system venture onto the street of the world, thus requiring detection and classification of bike images commonly found on the street. In reality, these classification systems face two types of problem (i) Objects of same category with large variation in appearance. (ii) The objects with different viewing conditions like occlusion, complex background containing buildings, trees etc. This study tries to bring out the importance of the background elimination with statistical based feature extraction method of varying sub block size for object classification.[10] Thus back ground removed and statistical features of squared sub blocks of the images are fed to the neural classifier. The objects of interest being a bike and non-bike images are classified.

Background removal and Mapping function

The overall complexity increases for the natural images as the object of interest is lying on the background region. In object classification problems it is essential to distinguish the object of interest and the background. Segmentation of object is done through background subtraction technique. This method is more suitable when the intensity levels of the objects fall outside the range of levels in the background. [10]

An object with natural background is figure. Initially morphological operations are applied to suppress the residual errors with help of open and close pair statements. The small regions are removed by filling the holes. Then the image subtraction is applied with the earlier result. Thus the object is segmented from the background. A mapping (I) is used to restore the object of interest from that of subtracted image.

$$f(x, y) = o, \text{ if } \quad d(x, y) = 0$$
$$I(x, y), \quad \text{otherwise}$$

Where f(x,y) is the transformed image, d(x,y) is image difference after fill operation and I(x,y) is the Original Image.


SPECTRAL FEATURES

Spectral measures of texture are based on the Fourier spectrum which is ideally suited for describing the directionality of periodic or almost periodic 2D patterns in an image. The global texture patterns are easily distinguishable as this spectral measure is a concentration of high energy bursts in the spectrum.

The spectral texture is useful for discriminating between periodic and non periodic texture patterns and for quantifying differences between periodic patterns. In this context the background segmented region of interest being bike images seems to have a periodic patterns and the natural scene seems to have non periodic patterns. The differences between periodic and non periodic patterns are utilized for classification purpose. [11]

$\theta)$ Interpretations of spectrum features are simplified by expressing the spectrum in polar coordinates yield a function S(r, $\theta)$ where S is the spectrum function and r and $\theta)$ are the variables in this coordinate system. For each direction $\theta)$ may be considered a 1 dimension function, s(r $\theta)$ similarly for each frequency r is 1 dimension function. Analysing S(r, $\theta)$ for a fixed value of $\theta)$ yields the behaviour of the spectrum along a radial direction from the origin, whereas analysing s(r $\theta)$ for a fixed value of r yields the behaviour along a circle centered on the origin. A global description is obtained by integrating these functions the following two equations.

$$S(r) = \sum_{\theta=0}^{\pi} S_{\theta}(r)$$
$$S(\theta) = \sum_{r=1}^{R} S_{r}(\theta)$$

Where R is the radius of a circle centered at the origin. The results of these two equations constitute a pair of values [S(r), S(θ)] for each pair of coordinates (r,θ). These coordinates are varied to generate two 1D functions, S(r), S(θ) that constitute a spectral energy description of texture for an entire image or region under consideration. Descriptors of these functions themselves can be computed in order to characterize their behaviour quantitatively. Descriptors typically used for this purpose are the location of the highest value, the mean and variance of the both the amplitude and axial variations and the distance between the mean and highest value of the function.

Thus spectral measures S(r) of texture are calculated for every sub block of an image. The feature vector varies with the size of the sub blocks chosen. The number of features populated by varying the block size.

Ridgelet Transforms

The ridgelet consturction divides the frequency domain to dyadic coronae |ξ|∈[2s, 2s+1]. In the angular direction, it samples the s-th corona at least 2s times. In the radial direction, it samples using local wavelets.

The ridgelet element has a formula in the frequency domain:[6]

$$\hat{\rho}_{\lambda}(\xi)=\tfrac{1}{2}|\xi|^{-\frac{1}{2}}\left(\hat{\psi}_{j,k}(|\xi|)\cdot\omega_{i,l}(\theta)+\hat{\psi}_{j,k}(-|\xi|)\cdot\omega_{i,l}(\theta+\pi)\right)$$

Wavelet Transform

The wavelet transform is similar to the Fourier transform (or much more to the windowed Fourier transform) with a completely different merit function. The main difference is this: Fourier transform decomposes the signal into sines and cosines, i.e. the functions localized in Fourier space; in contrary the wavelet transform uses functions that are localized in both the real and Fourier space. Generally, the wavelet transform can be expressed by the following equation:

Wavelet transforms are a mathematical means for performing signal analysis when signal frequency varies over time. For certain classes of signals and images, wavelet analysis provides more precise information about signal data than other signal analysis techniques. Wavelet Transform is classified into Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), and Fast Wavelet Transform (FWT).Generally, the wavelet transform can be expressed by the following equation [7]:

$$F(a,b)=\int_{-\infty}^{\infty} f(x)\,\psi^{*}_{(a,b)}(x)\,\mathrm{d}x$$

Where the * is the complex conjugate symbol and function ψ is some function. This function can be chosen arbitrarily provided that obeys certain rules.

Discrete Wavelet Transform

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT), or its implementation for the discrete time series sometimes called discrete-time continuous wavelet transform (DT-CWT).

The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions on them which are mentioned everywhere, e.g. the dilation equation [9]

$$\phi(x) = \sum_{k=-\infty}^{\infty} a_k \phi(Sx - k)$$

Where S is a scaling factor (usually chosen as 2). Moreover, the area between the function must be normalized and scaling function must be orthogonal to its integer translations, i.e.

$$\int_{-\infty}^{\infty} \phi(x)\, \phi(x+l)\, \mathrm{d}x = \delta_{0,l}$$

After introducing some more conditions (as the restrictions above does not produce unique solution) we can obtain results of all these equations, i.e. the finite set of coefficients ak that define the scaling function and also the wavelet. The wavelet is obtained from the scaling function as N where N is an even integer. The set of wavelets then forms an orthonormal basis which we use to decompose the signal. Note that usually only few of the coefficients ak are nonzero, which simplifies the calculations.

Discrete Cosine Transforms

The general equation for a 1D (*N* data items) DCT is defined by the following equation:

$$F(u) = \left(\frac{2}{N}\right)^{\frac{1}{2}} \sum_{i=0}^{N-1} \Lambda(i).cos\left[\frac{\pi.u}{2.N}(2i+1)\right] f(i)$$

Fast Fourier Transforms

An FFT computes the DFT and produces exactly the same result as evaluating the DFT definition directly; the most important difference is that an FFT is much faster. (In the presence of round-off error, many FFT [15] algorithms are also much more accurate than evaluating the DFT definition directly, as discussed below.)

Let x_0, ..., x_{N-1} be complex numbers. The DFT is defined by the formula

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k \frac{n}{N}} \qquad k = 0, \dots, N-1.$$

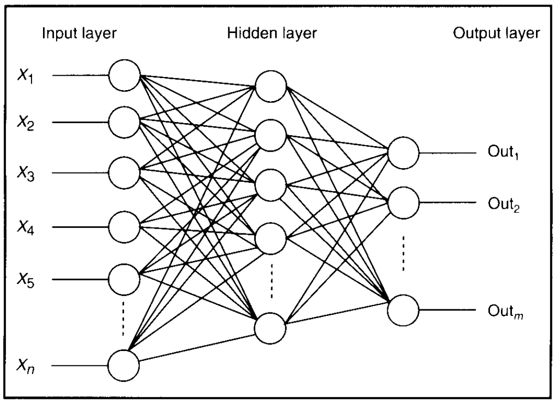
Evaluating this definition directly requires $O(N^2)$ operations: there are N outputs X_k, and each output requires a sum of N terms. An FFT is any method to compute the same results in $O(N \log N)$ operations.

BACK PROPAGATION METHOD

A binary artificial neural network classifier is built with back propagation algorithm that learns to classify an image as a member or non-member of a class.

The number of input layer nodes is equal to the dimension of the feature space obtained from the spectral features. The number of output nodes is usually determined by the application of Khotanzand and chung which is 1 either yes or no where a threshold value nearer to 1 represents Yes and a value nearer to 0 represents no. The neural classifier is trained with different choices for the number of hidden layer. The final architecture is chosen with single hidden layer shown in Fig .that results with better performance. The output neuron will be representing the existence of a particular class of object. [12]

$$O_j^1(k) = f[\sum_{m=0}^{N1-1} w_{jm}^1 O_m^{i-1}]$$



This study addresses the issues to classify objects of real world images containing side views of bike amidst background clutter and mild occlusion. The objects of interest to be classifier are bike (positive) and non bike (negative) images taken from Caltech standard database. The image data set consists of 4620 real images for training and testing having 826 in each class. The sizes of the images are uniform with the dimension 100X40 pixels. Database taken from

http://www.robots.ox.ac.uk/~vgg/data3.html
http://www.vision.caltech.edu/html-files/archive.html

The proposed frame work consists of two methods followed by hybrid of the wavelet and ridgelet transformations and hybrid of Discrete Cosine Transformations and Fast Fourier Transformations. Spectral features are calculated from each single block of sub image using equations mentioned earlier.

DISCUSSION

In object classification problem the four quantities of results category are given

True positive = classify a bike image into class of bike

True negative = Misclassify a bike image into class of non bike

False Positive = classify a non bike image into class of non bike image

False Negative = misclassify a non bike image into class of bike.

The object of any classification is to maximize the number of correct classification denoted by True positive and false positive rate where by minimizing the wrong classification denoted by True negative and False negative rate.

True positive rate = $\frac{No\ of\ true\ positive}{Total\ No\ of\ positive\ data\ in\ data\ set}$

True Negative rate = $\frac{No\ of\ true\ Negative}{Total\ No\ of\ Negative\ data\ in\ data\ set}$

False positive rate = $\frac{No\ of\ true\ false\ positive}{Total\ No\ of\ positive\ data\ in\ data\ set}$

False Negative rate = $\frac{No\ of\ \ false\ \ positive}{Total\ \ No\,of\ \ negative\ data\ \ in\ \ data\ set}$

The values of positive and negative used as testing samples are 400 and 400 respectively. Most classification algorithm includes a threshold parameter for classification accuracy which can be varied to lie at different trade off points between correct and false classification. The comparison of results of the proposed methods is shown below.

It is evident that the classifier with 40 blocks of size 10x10 is showing improved overall results 85.5 of classification accuracy comparatively with that of 10 blocks of size 20x20 which gives classification accuracy 84.2

CONCLUSION

Thus an attempt is made to build a system that classifies the objects amidst background clutter and mild occlusion is achieved to certain extent. Thus the goal to classify objects of real world images containing side views of bike with cluttered background with that of non bike images with natural scenes is presented. This complete study is implemented using neural network and image processing toolbox of mat lab 6.5.

REFERENCES

[1] Dongxiang Zhou, Hong Zhang and Nilanjan Ray,"Texture Based Background Subtraction," Proc. IEEE Int. Conf. on Information and Automation, Zhangjiajie, China, pp. 601-605, 2008.

[2] A. McIvor, "Background subtraction techniques," in Proc. Image Video Computing,pp. 147-153, 2000.

[3] Y. Ivanov, A. Bobick, and J. Liu, "Fast lighting independent background subtraction,"Int. Journal on Comp. Vision, vol. 37, no. 2, pp. 199–207, Jun. 2000.

[4] Pierre-Marc Jodoin, Max Mignotte and Janusz Konrad, "Statistical Background Subtraction Using Spatial Cues,"IEEE Trans. Circuits and Systems for Video Technology,vol. 17, no. 12, pp. 1758-1763, Dec 2007.

[5] G. Gordon, T. Darrell,M. Harville and J. Woodfill, "Background Estimation and Removal Based on Range and Color," Proc. IEEE Computer Society Conference on Comp. Vision and Pattern Recog.,Fort Collons,Jun 1999.

[6] Liyuan Li, Weimin Huang,Irene Yu-Hua Gu and Qi Tian, "Statistical Modeling of Complex Backgrounds for Foreground Object Detection," IEEE Transactions on Image Proc.,vol. 13, no. 11, pp. 1459-1472, Nov 2004.

[7] Wavelet Transform, chapter 4, Data processing and analysis

http://gwyddion.net/documentation/user-guide-en/wavelet-transform.html

[8] Richord J. Radke, Srinivas Andra, Omar Al-Kofahi and Badrinath Roysam, "Image Change Detection Algorithms: A Systematic Survey," IEEE Trans. on. Image Proces., vol. 14, no. 3, pp. 294–307, Mar 2005.

[9] Wavelet and Co-occurrence Matrix based Rotation Invariant Features for Texture Image Retrieval using Fuzzy Logic, Shailendrakumar M. Mukane, Dattatraya S. Bormane, Sachin R. Gengaje, International Journal of Computer Applications (0975 –8887) Volume 24– No.7, June 2011.

[10] The Landscape Toolbox , Unsu [10] B. Nagarajan and P. Balasubramanie, "Wavelet Feature based Neural Classifier System for Object Classification with Complex Background," Proc. IEEE CS International Conf. on Computational Intelligence and Multimedia Applications,vol. 1, pp.272-279, 2007.

[11] B. Nagarajan and P. Balasubramanie, "Neural Classifier System for Object Classification with Cluttered Background Using Invariant Moment Features," Int. Journal of Soft Computing, vol. 3, no. 4, pp. 302-307, 2008.

[12] B. Nagarajan and P. Balasubramanie, "Object Classification in Static Images with Cluttered Background using Statistical Feature based Neural Classifier," Asian Journal of Info. Tech., vol. 7, no. 4, pp. 162-167, 2008.

[13] B. Nagarajan and P. Balasubramanie, "Neural Classifier for Object Classification with Cluttered Background Using Spectral Texture Based Feature," Journal of Artificial Intelligence, vol. 1, no. 2, pp. 61-69, 2008.

[14] B. Nagarajan and P. Balasubramanie, "An Invariant Approach to Object Classification Using Background Removal," Proc. IEEE International Conference on Computing Communication and Networking, 2008

[15] Correlation-based Feature Selection for Machine Learning, Mark A. Hall, April 1999 Mark A. Hall

http://www.cs.waikato.ac.nz/~mhall/thesis.pdf

[16] R. Parivallal, Dr B.Nagarajan "Object identification method using maximum likelihood algorithm from Google map",IJRCAR vol no.2 issue 2, page no 153-159.

A Brief Author Biography

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