PERFORMANCE ANALYSIS OF CLASSIFIERS TO RECOGNITION OF OBJECTS FROM LOW-RESOLUTION IMAGES INDUSTRIAL SENSOR

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Abstract— Recognition of objects using images from industrial sensor is an important problem that has been motivated by the need for automatic recognition in industrial processes. An interesting issue is the automatic reading with high reliability in the classification of objects. Many alternatives can be used to accomplish with that, and in this context, this paper presents a comparison between k-Nearest Neighbors Classifier using Euclidean, City Block, Cosine and Correlation distance metric, the Self-Organizing Map (SOM) - Artificial Neural Network (ANN) and the Optimum-Path Forest, for classification of images taken from a low-resolution industrial sensor. Classification performance has been compared in terms of extraction time and accuracy using image analysis by Tchebichef moments.

Keywords— Computer vision and intelligent processing of images, Self-Organizing Map - Artificial Neural Network, Optimum-Patch Forest, Moment invariants.

1 Introduction

Machine vision provides innovative solutions in the direction of industrial automation. A lot of industrial activities have benefited from the application of machine vision technology on manufacturing processes. Machine vision technology improves productivity and quality management and provides a competitive advantage to industries that employ this technology (E. N. Malamas et al. 2003).

Thanks to the recent developments in data acquisition, processing, and process control systems, efficiency of many of the industrial applications has been improved with the help of automated visual processing and classification systems. Technological advances in digital image acquisition and processing have allowed building automated visual inspection systems (M. A. Selver et al. 2011). However, even with the rise of high-capacity computers, classification between the objects has proved to be a complex problem for machines.

In this context, this paper describes a comparison performance in terms of efficiency and processing time between the classifiers k-NN, Self-Organizing Maps - Artificial Neural Network and the Optimum-Path Forest aimed at improving the ranking process goals using images taken from a sensor with low resolution.

The remainder of the paper is directed as follows. Section 2 describes the feature extraction process. Section 3 gives an overview of supervised classification method. Section 4 discusses the results. Finally, section 5 concludes the paper with a brief discussion of future research.

2 Feature Extraction Process

Moments and moment functions have been extensively used for feature extraction in pattern recognition and object classification. One important property of the moments is their invariance under affine transformation.

Moments are scalar quantities used to characterize a function and to capture its significant features. From the mathematical point of view, moments are projections of a function onto a polynomial basis (J. Flusser et al. 2009).

M. K. Hu (1962), introduced the concept of moment, since then invariant moments and moment functions have been widely used in the fields of image analysis and pattern recognition. Hu's moment descriptors are invariant with respect to scale, translation and rotation of the image. However, the kernel function of geometric moments of order $(p + q)$, is not orthogonal, thus the geometric moments suffer from the high degree of information redundancy, and they are sensitive to noise for higher-order moments (D. Sridhar, Dr I. V. M. Krishna (2012).

R. Mukundan et al. (2001) introduced a set of discrete orthogonal moment functions based on the discrete Tchebichef polynomials. The implementation of Tchebichef moments does not involve any numerical approximation since its basis set is orthogonal in the discrete domain of image coordinate space. Tchebichef moments are thus expected to perform better than continuous moments, particularly in applications requiring the independent shape characteristics (V. J. Tiagrajah et al. 2011).

2.1 Tchebichef Moments

The discrete Tchebichef polynomials are defined for A. Erdelyi et al. (1953) and based on this polynomials, R. Mukunda et al. (2001) defined the scaled Tchebichef polynomials as

$$t'_p(x) = \frac{t_p(x)}{\beta(p,N)} \qquad (1)$$

p = 2, 3,..., N-1

where $t_p(x)$ is the discrete Tchebichef polynomial of degree p, given by

$$t_p(x) = (1-N)_p\, {}_3F_2(-p,-x,1+p;1,1-N;1), \qquad (2)$$

p, x, y = 0,1,2..., N-1

where $(a)_k$ is the Pochhammer symbol given by

$$(a)_k = a(a+1)(a+2)\ldots(a+k-1) \qquad (3)$$

and ${}_3F_2(\cdot)$ is the generalized hypergeometric function

$$ {}_3F_2(a_1,a_2,a_3;b_1,b_2;z) = \sum_{k=0}^{\infty} \frac{(a_1)_k(a_2)_k(a_3)_k\, z^k}{(b_1)_k(b_2)_k\, k!} \qquad (4)$$

and $\beta(p, N)$ is a suitable constant which is independent of x.

Under the above transformation, the squared-norm of the scaled polynomials gets modified according to the formula

$$\mathrm{P}(p,N) = \frac{\rho(p,N)}{\beta(p,N)^2} \qquad (5)$$

where

$$\rho(p,N) = \sum_{x=0}^{N-1}\{t_p(x)\}^2 \qquad (6)$$

Then, the Tchebichef moments are defined as

$$T_{pq} = \frac{1}{P(p,N)P(q,N)}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} t'_p(x)t'_q(y)I_{xy}, \qquad (7)$$

x, y = 0, 1,..., N - 1

When $\beta(p, N) = N^p$, we have the following recurrence formula for $t'_p(x)$

$$t'_p(x) = \frac{(2p-1)t'_1(x)t'_{p-1}(x) - (p-1)\left(1-\frac{(p-1)^2}{N^2}\right)t'_{p-2}(x)}{p}, \qquad (8)$$

p = 2, 3,..., N-1

where

$$t'_0(x) = 1 \qquad (9)$$

$$t'_1(x) = \frac{(2x+1-N)}{N} \qquad (10)$$

and

$$P(p,N) = \frac{N\left(1-\frac{1}{N^2}\right)\left(1-\frac{2^2}{N^2}\right)\cdots\left(1-\frac{p^2}{N^2}\right)}{2p+1}, \qquad (11)$$

p = 0, 1,..., N - 1

A plot of the polynomial values for N = 50, obtained from (8) is given in Figure 1.

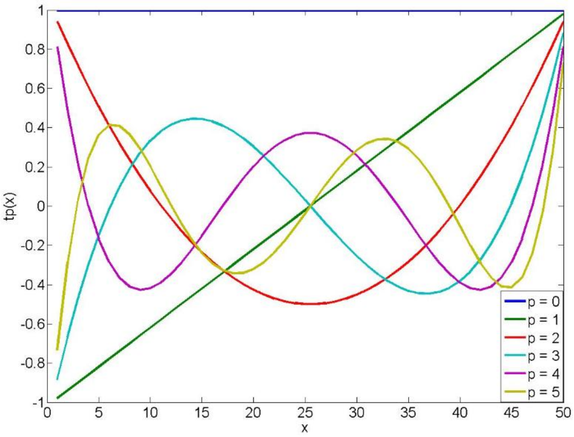

Figure 1. Plot of the Tchebichef polynomial to p=0,...,5 and N=50.

3 Supervised Classification

The final stage of any image-processing system where each unknown pattern is assigned to a category is the classification. The difficulty of the classification problem depends on the variability in the characteristic values of the objects of the same class.

Let's suppose that we have a classification problem in which there are M possible classes and there are N independent and identically distributed samples Z. The supervised classification problem consists in using that prior knowledge to classify new samples Zs to one of the M possible classes in a manner to minimize the classification error.

To do this a number of approaches are available, and some of them are discussed in this section and compared in the following.

3.1 k-Nearest Neighbors Classifier

The k-Nearest Neighbor rule (kNN) is one of the best known methods for supervised pattern recognition in analytical chemistry and, more generally, the method has been proposed by T. M. Cover (1968) as a reference method for the evaluation of the performance of more sophisticated techniques (D. Coomans, D. L. Massart (1981)).

In general the following steps are performed for kNN algorithm:

1. Choose of k value: k value is completely up to user. Generally after some trials a k value is chosen according to results.

2. Distance calculation: Any distance measurement can be used for this step.

3. Distance sort in ascending order: Chosen k value is also important in this step. Found distances are sorted in ascending order and k of minimum distances are taken.

4. Classification of nearest neighbors: Classes of k nearest neighbor are identified.

3.1.1 Distances

As shown in step 2, we can use various distances.

Euclidean Distance

Let's considerer the two input variable case since it is easy to represent in two-dimensional space. The distance between these two points is computed as the length of the difference points, is denoted by

$$d(x,x') = |x - x'| = \sqrt{(x_1 - x'_1)^2 + (x_2 - x'_2)^2} \quad (12)$$

City Block Distance

The City Block distance between two points, x and x', with k dimensions is calculated as

$$d(x,x') = \sum_{j=1}^{k} |x_j - x'_j| \quad (13)$$

Cosine Distance

The Cosine distance between two points

$$d(x,x') = 1 - \frac{\sum_{i=0}^{k}(x_i x'_i)}{\sqrt{\sum_{i=0}^{k}(x_i)^2 \sum_{i=0}^{k}(x'_i)^2}} \quad (14)$$

Correlation Distance

The Correlation distance between two points

$$d(X,X') = 1 - \frac{\sum_{i=0}^{k}(X_i - \overline{X}_i)(X'_i - \overline{X}'_i)}{\sqrt{\sum_{i=0}^{k}(X_i - \overline{X}_i)^2 \sum_{i=0}^{k}(X'_i - \overline{X}'_i)^2}} \quad (15)$$

3.2 Optimum-Path Forest (OPF)

J. P. Papa et al. (2009) introduced the idea of designing pattern classifiers based on optimum-path forest that was developed as a generalization of the Image Foresting Transform (IFT) (A. X. Falcão et al. (2004). OPF is simple, multi-class, parameter independent, does not make any prior assumption about the shapes of classes and can handle some degree of overlapping (R. Souza et al. 2012).

This classifier is based on a forest of optimal paths, which is constructed by calculating the maximum of the shortest paths between the samples and the prototypes of classes. The path cost is computed from the distances between the feature vectors of the samples.

The OPF is divided into two steps, adjustment and prediction. Adjustment corresponds to the learning stage. The main components of OPF are calculated: Minimum Spanning Tree, prototypes and the cost matrix samples compared to the prototypes.

In the Prediction step, new samples are classified using the forest paths resulting from the large stage of adjustment.

The OPF classifier reduces the problem of classification standards for a partitioning problem in a graph. Prototypes chosen initially begin a process of conquest in the graph, offering optimal cost paths to the other samples. A path cost function is defined, associating to each path in the graph the cost of considering all objects along the way as belonging to the same class. Thus, the graph is partitioned into a forest of optimal paths whose roots are the prototypes.

The training consists essentially in building these great forest paths where the objects in a given OPF will have the same label its prototype, in other words, the same class from the root of the tree of which it belongs to. To classify an object in the training set, we evaluate the optimal paths from prototypes to it in order to find which OPF will win the element to be classified. The label of this tree is associated with the object under test.

3.3 Self-Organizing Map (SOM)

Self-Organizing Map (SOM) (T. Kohonen (1990)) is an unsupervised neural network that has the ability to perform clustering and preserve the topology (S. Wu, T. W. S. Chow (2004)) of the data.

The general equation utilized, at this paper, to update the neurons is as follows (S. Haykin (2001))

$$w_i(t+1) = w_i(t) + \eta(t)h(i^*, i, t)[x(t) - w_i(t)] \quad (16)$$

in which $w_i(t+1)$ is the new neuron weight, $\eta(t)$ is the learning rate and $h(i^*, i, t)$ is the neighborhood function. The learning rate varies according to

$$\eta(t) = n_0\left(1 - \frac{t}{t_{max}}\right), \tag{17}$$

where $0 < n_0 < 1$, t is the current iteration and t_{max} is the total number of iterations.

The neighborhood function varied according to:

$$h(i^*, i, t) = \exp\left(-\frac{\|r_i(t) - r_{i*}(t)\|^2}{2 \propto^2 (t)}\right) \tag{18}$$

where i^* is the current winner neuron, $\|r_i(t)\text{-}r_{i*}(t)\|$ is the squared Euclidian distance between the current neuron and the current winner neuron, and $\propto^2$ determines the influence of the winner neuron over the others.

This neural network can also be used as a classifier.

At the end of its training, the data are shown to the network again, and each neuron is labeled as a representative of some class. The choice of the class to which the neuron will be labeled is by counting the number of data of this class, for which the neuron was the winner.

4 Results and Discussion

The hardware used for image acquisition in this work was the 50x64 resolution 3D sensor effector pmd E3D200, from ifm electronic®. It contains Ethernet interface, thus allowing for implementation of remote and eventually real-time applications of classification algorithms. The device has been used to acquire images of three packages with a few differences in size, as shown in Figure 2, 3 and 4.

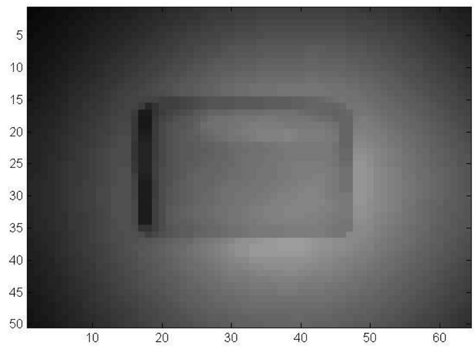

Figure 2. Package 1 with dimension 15×10.5×7.2 cm.

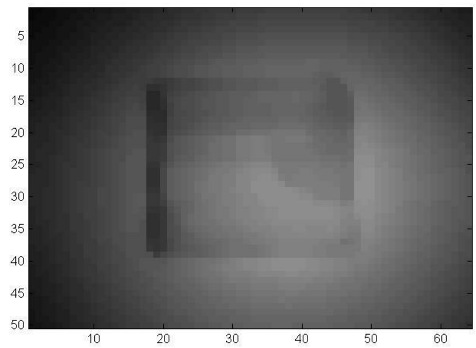

Figure 3. Package 2 with dimension 15×14×6 cm.

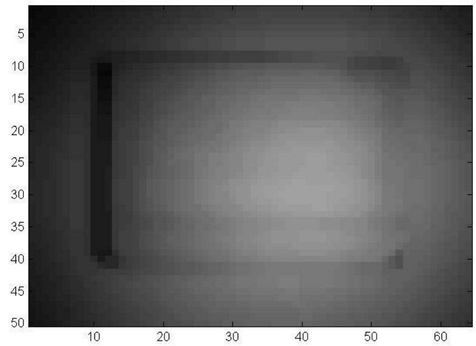

Figure 4. Package 3 with dimension 21.5×16.2×9.6 cm.

It is worth lighting that the experiments are based on three classes. The number of prototypes per class is 6, referring to the 6 sides of each box, so, the database contains 18 objects.

In our experiments, the number of input features extracted and the processing times per 50 times is shown in Table I, where **Min**, **Max** and **STD** indicates Minimum, Maximum and Standard Deviation.

Table I. Number of input × Processing Times of the Tchebichef moment.

Number of Input	**Times (seconds)**				
	Min	**Max**	**Mean**	**Median**	**STD**
36	0.537	0.7048	0.5527	0.5501	0.0234

These input vectors are presented to the classifiers. The classifiers have been trained and tested 150 times with the same database. Experimental results plotted in figure 5 show the performance of the kNN classifier for different choices of distance calculation; The processing times are reported in Table II

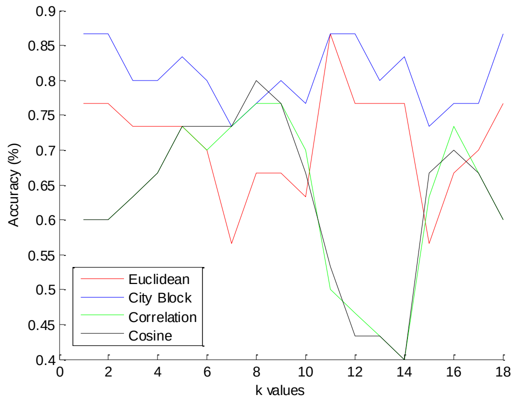

Figure 5. Accuracy of the kNN classifier.

Among the various choices, the one based on the City Block distance obtained the best hit rates for variations in k between 1-18. His hit rate was: minimum = 73.33%, maximum = 86.67%, mean = 80.74% , median = 80% and standard deviation = 4.652.

The Table II shows their times to complete the classification for the values of k = 1, 5, 10 and 18.

Table II. Processing Times to the Classification.

kNN City Block	Times (seconds)				
	Min	Max	Mean	Median	STD
1	0.0015	0.0032	0.0021	0.0016	0.00024
5	0.0017	0.0036	0.0019	0.0018	0.00026
10	0.0023	0.0027	0.0025	0.0024	0.00007
18	0.0031	0.0035	0.0032	0.0032	0.00010

Tables III, IV and V show training times, elapsed times for classification and accuracy values, respectively, of OPF classifier and the SOM-ANN classifier.

Table II. Processing Times During Training Stage.

	Times (seconds)				
	Min	Max	Mean	Median	STD
OPF	0.00011	0.00019	0.00014	0.00014	0.00001
SOM ANN	0.21030	0.51630	0.2290	0.22350	0.03190

Table III. Processing Times for Classifying

	Times (seconds)				
	Min	Max	Mean	Median	STD
OPF	0.00006	0.00023	0.00018	0.00018	0.000012
SOM ANN	0.00100	0.00190	0.00110	0.00100	0.000172

Table IV. Accuracy

	Accuracy(%)				
	Min	Max	Mean	Median	STD
OPF	82.5	90	83.62	82.5	2.686
SOM ANN	67.6	80	76.7	75.2	3.328

For the proposed problem in this work, all classifiers proved to be compatible with real time general requirements for industrial process classification.

SOM-based classifier spent more time during classification, and this is due to the fact that this classifier has more parameters than the classifier based on graph, OPF, which is free of parameters.

This neural network also presented lower hit rates, mainly due to the fact that the first 2 classes have really similar values.

A difficulty faced when using SOM Classifier was the short training data set. Since Tchebichef Moment, is invariant to rotation, scaling and translation, it emerged very laborious to get new samples and only 6 training data for each class (sides of each box) have been used.

On the other hand, even with such a short training data set, OPF classifier performed well, achieving a maximum rating of 90% with short classification and training times for the application considered

5 Conclusions

This paper introduced a comparative study between 3 classifiers methods: kNN using Euclidean, City Block, Cosine and Correlation distance; Self Organizing-Map – ANN; and Optimum-Path Forest to image recognition from industrial sensor using Tchebichef moment approach to feature extraction.

At this writing, the best results with this technique of feature extraction has been through the OPF classifier, which proved to be fast and efficient for the problem at hand.

A second alternative would be to use the kNN classifier, based on City Block distance, which proved an accuracy rate of 86.67% and a minimum time for training and classification. Another fact that makes it attractive for application is the extensive literature found on it and its easy implementation.

In the near future, classifiers based on supervised neural networks such as MLP can be tested.

Acknowledgment

Authors acknowledge CAPES for financial support. FUNCAP has also supported this work (PP1-0033-00032.01.00/10).

Authors thank Rockwell Automation do Brasil, for the support through the Scientific and Technical Cooperation Agreement with the Federal University of Ceará and, finally, NUTEC, for administrative facilities.

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