ijecs open access www.ijecs.in
International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 3 Issue 2 February, 2014 Page No. 3986-3990

A Efficient Approach Used for Identifying Distraction of statue Image

C.Kanimozhi[1], Dr.A.Gnanabaskaran
PG scholar [1]departmentof computer science and engineering,
K.S.Rangasamycollege of technology,
ckanikani@gmail.com
M.E,Phd [2]
[2]departmentof computer science and engineering,
K.S.Rangasamy college of technology,

Abstract
In this study, we mainly concentrate on measuring the different features of statues inorder to maintain it'svolubility.There is a need to maintain valuable status in our world from the possible disasters. For this purpose, a different part of the image is captured and its parametric values were validated with the pre available dataset of those statues.The main objective of this paper is to rebuilt the originality of the statues in case of any damages. The technique to be used here is Artificial neural network inorder to estimate its different parameters incase of any damage.

1.Introduction

The number of statues in world are getting destroying withevery passing day, due to disaster .The computer-aided studies for the maintaining the statues becomes more important Different features or parameter measurement of an images were obtained from available dataset. The parameter measurement includes statues height, weight, width of an each and every individual parts of statue. Artificial neural network approach is used.

Recently, there is development in image processing systems, techniques and applications. One of the opportunities enabled by these visual applications is the ability of making measurements from the taken images. The machine vision applications in electronic systems have been used increasingly in industrial area day by day. The contactless analysis of substances is preferred more than other methods, because destructions, variations or undesired negative variations might occur on the substance which is measured in contact.

The system implements the analysis of Artificial Neural Network's (ANN's) neural fitting tool (Nftool) methodology. The Availabledataset value is given as an input to the Artificial Neural Network analysis of MATLAB's neural fitting tool (Nftool). Then the network will be trained well until got a high performed, low error rated and good regression plot. Then we get an output for any future inputs.

In paper[1], body measurements (BMs) of Holstein cows were determined using digital image analysis (IA) and these were used to estimate the live weight (LW) of each cow. For this purpose, an image capture arrangement was established in a dairy cattle farm. BMs including wither height (WH), hip height (HH), body length (BL), hip width (HW), plus the LWs of cows were first determined manually, by direct measurement [2]. Then the digital photos of cows were taken from different directions synchronously and analyzed by IA software to calculate WH, HH, BL and HW of each cow.

In our proposed system, neural fitting tool is used. The tool which is available in matlab.In which high accurate result will be produced.Nftool use Levenberg–Marquardt algorithm for training.By changing number of neuron the more accurate result will be produced.For each training different output value will be produced. The network will be trained with Levenberg-Marquardt backpropagation algorithm (trainlm), unless there is not enough memory, in which case scaled conjugate gradient backpropagation (trainscg) will be used.

2.Artificial neural network

Artificial neural network operate in the same way as the brain's neural network and use interconnected nodes (called neurons) to transfer information. ANN structure is divided into three segments: input layer, hidden layer, and output layer fig 1.The number of neurons in the input and output layer is fixed to be equal to that of input and output variables, respectively, whereas the hidden layer can contain more. than one layer, and in each layer the number of neurons is flexible. In the hidden layers as well as in the output layer, the individual neuron acquires the information from the neurons in the former layer, and transforms the information.

There is no single formal definition of what an artificial neural network is, Generally, it involves a network of simple processing elements exhibiting complex global behavior determined by the connections between the processing elements and element parameters. Commonly, though, a class of statistical models will be called "neural" if they

1. consist of sets of adaptive weights, i.e. numerical parameters that are tuned by a learning algorithm
2. capable of approximating non-linear functions of their inputs.

The adaptive weights are conceptually connection strengths between neurons, which are activated during training and prediction. Neural networks are also similar to biological neural networks in performing functions collectively and in parallel by the units, rather than there being a clear delineation of subtasks to which various units are assigned. The term "neural network" usually refers to models employedin statistics, cognitive psychology and artificial intelligence. Neural network models which emulate the central nervous system are part of theoretical neuroscience and computational neuroscience.

3.Levenberg-Marquard algorithm

LevenbergMarquardalgorithm, provides a numerical solution to the problem of minimizing a nonlinear function. It is fast and has stable convergence. In the artificial neural-networks field, this algorithm is suitable for training small- and medium-sized problems. Many other methods have already been developed for neural-networks training. The steepest descent algorithm, also known as the error backpropagation (EBP) algorithm, dispersed the dark clouds on the field of artificial neural networks and could be regarded as one of the most significant breakthroughs for training neural networks. Many improvements have been made to EBP, but these improvements are relatively minor . The EBP algorithm is still widely used today; however, it is also known as an inefficient algorithm because of its slow convergence

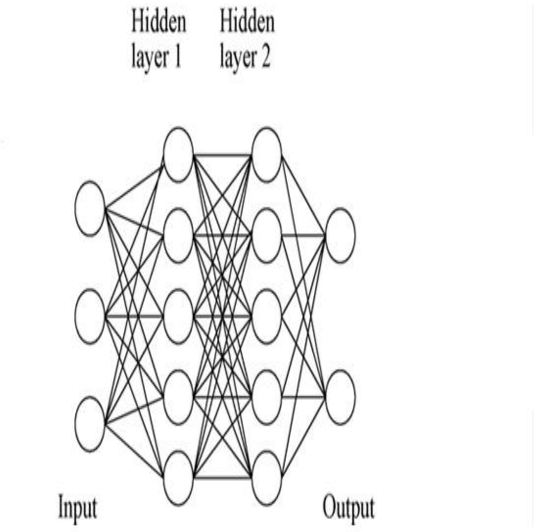

Figure 1 Network architecture.

There are two main reasons for the slow convergence: the first reason is that its step sizes should be adequate to the gradients. Logically, small step sizes should be taken where the gradient is steep so as not to rattle out of the required minima (because of oscillation). So, if the step size is a constant, it needs to be chosen small. Then, in the place where the gradient is gentle, the training process would be very slow. The second reason is that the curvature of the error surface may not be the same in all directions, such as the Rosenbrock function, so the classic "error valley" problem may exist and may result in the slow convergence. The slow convergence of the steepest descent method can be greatly improved by the Gauss–Newton algorithm. Using second-order derivatives of error function to "naturally" evaluate the curvature of error surface, The Gauss–Newton algorithm can find proper step sizes for each direction and converge very fast; especially, if the error function has a quadratic surface, it can converge directly in the first iteration. LevenbergMarquardalgorithm, provides a numerical solution to the problem of minimizing a nonlinear function. It is fast and has stable convergence

4.Comparison of Algorithms

The advantage of the Levenberg–Marquardt algorithm,let us use the parity-3 problem and make a comparison among the EBP algorithm, the Gauss–Newton algorithm, and the Levenberg algorithm. Three neurons in multilayer perceptron network are used for training, and the required training error is 0.01. In order to compare the convergent rate, for each algorithm, 100 trials are tested with randomly generated weights (between −1 and 1).

The training results and the comparison is presented in Table 1.2. One may notice that: (1) for the EBP algorithm, the larger the training constant α is, the faster and less stable the training process will be; (2) Levenberg–Marquardt is much faster than the EBP algorithm and more stable than the Gauss–Newton algorithm. For more complex parity-*N* problemlegzzs, the Gauss–Newton method cannot converge at all, and the EBP algorithm also becomes more inefficient to find the solution, while the Levenberg–Marquardt algorithm may lead to successful solutions Table 2.1.

Table 2.1 Traning patterns of theparity 3 problems

INPUT			OUTPUT
-1	-1	-1	-1
-1	-1	1	1
-1	1	-1	1
-1	1	1	-1
1	-1	-1	1
1	-1	1	-1
1	1	-1	-1
1	1	1	1

TABLE 2.2 Comparsion among different

Image total height (pixels)	Image total weight (pixel)	Body Weight (pixel)	Body Heigh (pixel)	Body Width (pixel)	leg height (pixel)	Leg width (pixel)
150	1000	680	100	250	40	26
180	1500	900	120	290	70	39
200	2000	1000	180	370	110	74
250	2800	1600	190	410	120	63
300	3100	2500	250	530	190	88

algorithms for parity-3 problem

5.Nf tool (Neural fitting tool)

Algorithm	Convergence Rate(%)	Average Iteration	Average Time(ms)
EBP algorithm(α=1)	100	1646.52	320.6
EBP algorithm(α=1)	79	171.48	36.5
Gauss-Newton algorithm	3	4.33	1.2
Lenvenberg-Marquard algorithm	100	6.18	1.6

The Neural Network Fitting Tool will help you select data, create and train a network, and evaluate its performance using mean square error and regression analysis. A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons (fitnet), can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer.The network will be trained with Levenberg-Marquardt backpropagation algorithm (trainlm), unless there is not enough memory, in which case scaled conjugate gradient backpropagation (trainscg) will be used.

For example Let us consider thetiruvalluvar image. Different parameter of statue are taken.The parameter like height,width,weight of different parts of statue.The dataset value are trained by using nftoolThe network should be trained until good regression point and low error rate**.**During training three types of operation
are performed training validation , testing.

3.1 Parameter value

5.1Training

These are presented to the network during training, and the network is adjusted according to its error.

5.2 Validation

These are used to measure network generalization, and to halt training when generalization stops improving.

5.3 Testing

These have no effect on training and so provide an independent measure of network performance during and after training.

Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error.

Regression R Values measure the correlation fig (1.2) between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship.After the network is trained simulation link (simulink) diagram is produced. It gets the input in the format of matrix. It is the expected value or unknown values. The simulink diagram should be run after getting the input, and then the output box is clicked to generate the graph.After getting the result the simulink will be stored for future access. Here the input and target mainly focused on finding the mass difference value.

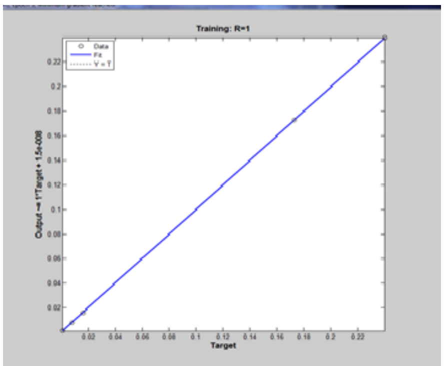

Fig: 1.2 Rregression plot

Conclusion and future work:

There is a need to maintain valuable status in our world from the possible disasters. For this purpose, different parts of the image is captured andits parametric values were validated with the pre available dataset of those statues. The main objective of this paper is to rebuilt the originality of the statues in case of any damages. The technique to be used here is Artificial neural network inorder to estimate its different parameters incase of any damage.

The problems related to costs, difficulties, personnel, risks andstresses encountered during the measurement and will be solved by using the Artificial neural network method. In future work many other parameter will be used for training. Which will give more accurate result.

REFERENCE:

[1] Abdullah Urkmezb,SakirTasdemira, serefInal(2010),"Determination of bodymeasurements on the Holstein cows using digital image analysis and estimation of live weight with regression analysis", Computers and Electronics in Agriculture 76 189–19.

[2] Bianconi ,Finzi, A ,Negretti, P(2007 "Visual image analysis to estimate morphological and weight in rabbits" World Rabbit Sci. 15, 37–41.

[3] Chedad,Wet, L.D., Vranken, E.Aerts, J.M., Ceunen, J., Berckmans(2003), "Computer-assisted image analysis to quantify daily growth rates of broiler chickens.Br. Poult. Sci. 44, 524–532.

[4]Enevoldsen,C,Kristensen,T,(1997),"Estimation of body weight from body size measurements and body condition scores in dairy cows", J. Dairy Sci. 80, 1988–1995.

[5] Fausett L. (2007),"Fundamentals of neural networks, architectures, algorithms and appications", New Jersey: Prentice Hallvol76 189–19.

[6] Inal, Tasdemir, Urkmez,Yakar (2008)," Determination of body measurements of a cow by image analysis", In: CompSys Tech'08, International Conference on computer science.

[7] Mutluoglu, Yakar, M, Yilmaz, H.MO(2010),"Close range photogrammetry and robotic total station in volume calculation", Int. J. Phys. Sci. 5, 086–096

[8] Ozkaya, S, Yalcin, B., (2008),"The relationship of parameters of body measures and body weight by using digital image analysis in pre-slaughter cattle. Arch. Tierz", Dummerstorf 51, 120–128

[9]Wang,Y.,Walker,L,Winter,P.Yan (2008) " Walk-through weighing of pigs using machine vision and an Artificial neural network". Biosyst. Eng. 100,117–125.

[10] Yilmaz, H.M., Yakar, M., Yildiz, F.,(2008) ,"Digital Photogrammetry in obtaining of 3D Model Data of Irregular Small surfaces Objects", ISPRS Congress , Beijing, pp. 125–130.

[11] KaiminYu ,ZhiyongWang , LiZhuo , JiajunWang, ZheruChi , DaganFeng (2013)," Learning realistic facial expressions from web images", Pattern Recognition 46 (2013) 2144–2155

[12]S. PadamPriyal ,PrabinKumarBora(2013)",A robust static and gesture recognition system using geometry based normalizations and Krawtchouk moments", Department ofElectronicsandElectrical Engineering,IndianInstituteofTechnologyGuwahati 78103.