Effective Surveillance Image Analysis using Combination of Linear Regression Model and Modified Probabilistic Neural Network

Tony Jan, Aneesh Krishna, Massimo Piccardi, and Thomas Hintz
Computer Vision Group,* University of Technology, Sydney
P.O. Box 123, Broadway, NSW, Australia

Abstract

In this paper, a hybrid model is introduced which combines a linear regression model in parallel with a nonlinear regression model such as the Modified Probabilistic Neural Network (MPNN). This model provides a first order approximation of the underlying mechanism using linear regression, and then use the MPNN to capture the local details of interest. This model allows the selected data regions of interest be modeled more accurately by a nonlinear compensator while the rest of the data regions are approximated by a linear regression model. The experiment on surveillance image modelling shows that the proposed model achieves improved performance over conventional methods such as MultiLayer Perceptron (MLP) or Volterra Filter based modelling.

Keywords: visual surveillance, image analysis, neural network

1 Introduction

In visual surveillance applications, efficient image processing techniques are very important due to intensive computations required. Many methods have been proposed to achieve efficiency in visual information processing from various disciplines such as Engineering, Statistics and others. In this paper, we propose a hybrid modelling system that models the surveillance images in two separate signal spaces in order to achieve reduced complexities while achieving satisfactory modelling performance.

In many surveillance image processing applications, it is reasonable to assume that the region of interest within the image may only be the small region where the human subject is located. If a nonlinear modelling technique is utilized to model the whole details of the image, it is clearly ineffective since many redundant information must also be modeled in detail. In such cases, it is reasonable to approximate the coarse grained overall structural background information of the image firstly by a linear regression model, and then to apply a nonlinear regression model to obtain the fine grained model of the significant information such as the human location or movement that require attention. The nonlinear model approximates significant human related information by modelling the local complexities which are represented by the difference between the linear approximation of the image and the training sample image. This allows the selected local regions of interest (e.g. human location) to be modeled more accurately by a nonlinear model in a separate domain (see figure 4-3), whilst the rest of the regions are approximated adequately by the linear regression model utilizing all available data (see figure 4-2). This method promises to be very effective and efficient especially for large image processing applications by reducing the computational complexity while achieving good modelling performance.

The proposed hybrid system is a parallel combination of a linear regression model and the Modified Probabilistic Neural Network (MPNN). In this hybrid model, the linear regression model provides a reasonable structural approximation of the underlying image, while the MPNN approximates the human-related complexities occuring in specific regions of the image by effectively adjusting a single smoothing parameter[1]. This model achieves superior modelling performance over conventional nonlinear modelling techniques such as the MultiLayer Perceptron (MLP) and Volterra Filters.

2 Method

The model is a linear regression model connected with MPNN in parallel as shown in Figure 2, and described in equations 1 and 2.

$$\widehat{y}(X) = [w_o + \underline{W}\,\underline{x}] + \left[\frac{\sum Z_i y_{N_i} f_i(\underline{x} - \underline{c}_i, \sigma)}{\sum Z_i f_i(\underline{x} - \underline{c}_i, \sigma)}\right] \quad (1)$$

where

$$y_{N_i} = y_i(\underline{x}_i) - [w_o + W_i \underline{x}_i] \quad (2)$$

and

$\underline{x}$= input vector,

$\underline{x}_i$= training input vector,

y_i = scalar training output,

y_{N_i}= difference between the linear approximation and the training output,

$\underline{c}_i$ = center vector for class i in the input space,

Z_i= no. of vectors $\underline{x}_i$associated with each $\underline{c}_i$,

w_o= initial offset,

W_i= weights of the linear model.

The linear regression model is firstly approximated by using all available training data in a linear regression analysis. Then the MPNN is constructed to compensate for the local nonlinearities. The local nonlinearities are represented by the difference between the linear regression output and the training output data as shown in equation 2.

*email:jant@it.uts.edu.au

[1]Spread value used for General Regression Neural Network or Modified Probabilistic Neural Network.

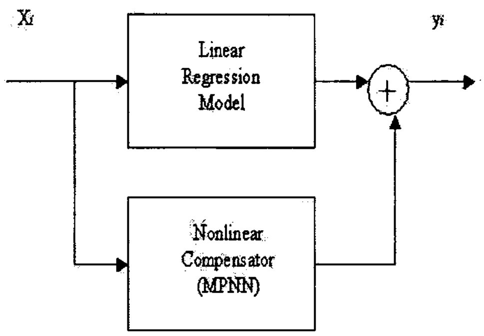

Figure 1: Combination of Linear Regression Model with MPNN as Nonlinear Regression Model

2.1 Introduction to MPNN

The MPNN was initially introduced by Zaknich et al [1991]. It is closely related to Specht's GRNN and his previous work, Probabilistic Neural Network (PNN) [Specht 1990]. The basic MPNN and GRNN methods have similarities with the method of Moody and Darken [1988]; the method of RBF's [Powell 1985], [Broomhead 1988]; the CMAC [Albus 1975], [Miller et al. 1990]; and a number of other nonparametric kernel-based regression techniques stemming from the work of Nadaraya and Watson [1964].

The general algorithm for the MPNN is:

$$\widehat{y}(\underline{x}) = \frac{\sum_{i=0}^{M} Z_i y_i f_i(\underline{x})}{\sum_{i=0}^{M} Z_i f_i(\underline{x})} \quad (3)$$

with

$$f_i(\underline{x}) = exp\frac{-(\underline{x}-\underline{c}_i)^T(\underline{x}-\underline{c}_i)}{2\sigma^2} \quad (4)$$

$\underline{x}$= input vector,
y_i = scalar training output,
$\underline{c}_i$ = center vector for class i in the input space,
Z_i= no. of vectors $\underline{x}_i$associated with each $\underline{c}_i$
M = number of unique centers $\underline{c}_i$

A Gaussian function is often used for $f_i(\underline{x})$ as defined in equation 4, however many other suitable radial basis functions can be used. Tuning simply involves finding the optimal σ giving the minimum mean squared error (mse) of the network output minus the desired output for a representative tuning set of known sample vector pairs by a convergent optimization algorithm [Zaknich et al. 1991].

The MPNN can approximate arbitrary functions to a predetermined acceptable accuracy by adjusting a single smoothing parameter. Another important advantage of the MPNN is that its output is guaranteed to reduce to zero for the inputs which are not represented in the training data set. This property of MPNN makes it a very good candidate as a nonlinear compensator.

2.2 Nonlinear compensator

Linear regression model offers many advantages over nonlinear ones especially for weakly nonlinear adaptive applications [Hayes 1996]. Linear models, especially in Finite Impulse Response (FIR) form, can be guaranteed to be stable, fully analyzable and can also be adapted quickly. For nonlinear problems, some higher order models can be used but their adaptation, computation time and complexity increases very quickly. A practical solution to this problem is to retain the linear part of the modelling and replace the second or higher ordered modelling part with a simpler nonlinear model algorithm such as MPNN.

The MPNN part will only model nonlinearities which have been defined by the difference between the linear model and the training data. Any data which is outside this training data will produce a zero effect from the MPNN/GRNN and the linear model will dominate. The linear modelling can be achieved using the standard least mean square error rule. The MPNN adaptation can be achieved as described in subsection 2.1.

The advantages of this model are:

1. There is a strong underlying linear influence to model the structural information of the underlying image.
2. The MPNN embodies a simpler nonlinear function approximation, modelling only the small abrupt changes.
3. The MPNN can be more efficient than higher order Volterra realizations.
4. The system is quick and easy to model any arbitrary nonlinear systems.

3 Experiment

Consider the image in Figure 2 which shows the human subject in a typical surveillance image.

Figure 2: Large Scale Visual Surveillance Image

Figure 3 shows the gray level values of the pixels in the 320th row from the image in Figure 2. For clear display, we are showing only a one dimensional view, however extension to multidimensional is straightforward.

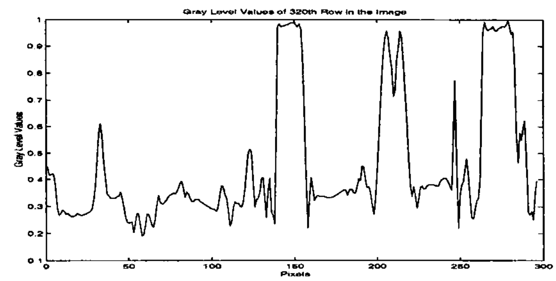

Figure 3: Gray Scale Level of Pixels from the 320th Row of Surveillance Image

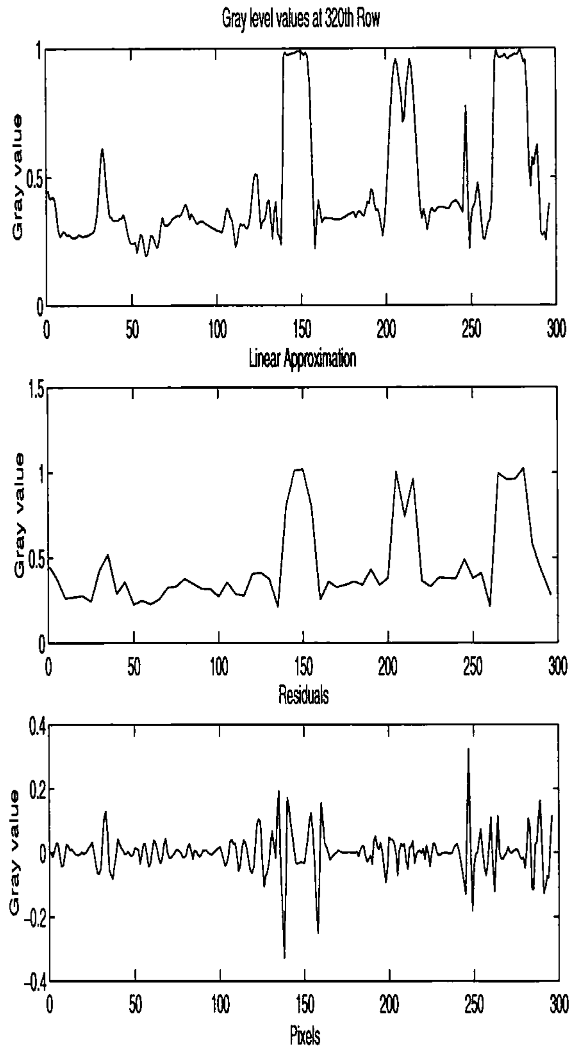

Figure 4-1: Original Grayscale values from image
Figure 4-2: Piecewise linear regression output
Figure 4-3: The Difference/Residuals

The structural background information of the image in Figure 3 can be approximated by a piecewise linear model (Figure 4-2). The difference between the actual scene and the background approximation (Figure 4-3) is then learnt by the MPNN.

The difference in Figure 4-3 represents high frequency lumination variations in space which provide useful information for image analysis. For example, small spots of interests such as number plates on the cars or human can be readily detected from Figure 4-3. The residual or difference information presented in Figure 4-3 still requires post-processing methods such as the shape analysis or some pattern recognition methods to infer semantic significance of some particular patterns. It is evident that those patterns can be readily extracted from Figure 4-3. In this paper, however we only concentrate on the modelling of residuals. Effective pattern recognition can be easily followed from effective modelling in further experiments.

4 Results and Analysis

A few conventional modelling techniques have been compared and their modelling performances are presented in this section. The modelling performance is measured by the difference between the desired (real) output (Figure 4-3) and the approximation obtained by the particular modelling technique. More comparisons are made on the basis of their training and testing time, and finally their overall effectiveness as a nonlinear compensator.

4.1 Volterra filters as a nonlinear model

Volterra filters for nonlinear modelling are frequently used in various fields such as signal processing, communication and image processing [Krusienski 2001]. In many practical problems, Volterra filters of higher order than three are seldom used due to very large computation and slow convergence.

We used a third order Volterra filter to model the given surveillance image.

MSE	Training Time	Testing Time
-22 dB	119 seconds	9 seconds

Table 1: The performance of Volterra filter as a nonlinear compensator

The MSE from the network using the third order Volterra filter was -22 dB. The nonlinear modelling performance was acceptable however the long training and testing time makes it difficult to use this method in real time visual surveillance (image processing) applications.

4.2 MLP as a nonlinear compensator

MultiLayer Perceptron (MLP) is a well-recognised nonlinear modelling technique. MLP has proven successful in speech recognition and others [Haykins, 1996]. For details on MLP see [Haykins, 1996].

For our experiment, the MLP architecture was chosen empirically as a 20-5-1 network (1 input layer with 20 neurons, 1 hidden layer with 5 hidden neurons, and 1 output layer with 1 neuron).

MSE	Training Time	Testing Time
-40 dB	91 seconds	4 seconds

Table 2: The performance of MLP as a nonlinear compensator

The MSE for the network of a linear regression model and a MLP was -40 dB. The nonlinear modelling performance was improved by two orders from Volterra modelling. However MLP did not prove to be an effective nonlinear compensator due to its unpredictable output for the inputs which are outside the region of interest (local nonlinear regions). The output of a nonlinear compensator was required to reduce to zero for the input which is outside the selected nonlinear region, in order for the network to utilise its best linear fit for those regions (refer section 2-2). MLP did not prove to be an effective nonlinear compensator because the MLP produced an unpredictable output for the inputs that are outside the selected nonlinear regions, degrading overall performance as a hybrid model.

4.3 MPNN as a nonlinear compensator

In our experiment, Gaussian function was used as the radial basis function. Refer section 2.1 for details on MPNN architecture. Table 3 shows the performance of MPNN combined with a linear regression model:

MSE	Training Time	Testing Time
-36 dB	12 seconds	6 seconds

Table 3: The performance of MPNN as a nonlinear compensator

The MSE of the network of a linear regression model and a MPNN was -36 dB. The nonlinear modelling performance was comparable to MLP. MPNN proved be a better nonlinear compensator by effectively reducing the MPNN output to zero for the inputs outside the region of interest, allowing the linear regression model to estimate the best fit. The training and testing time were acceptable for the given task.

5 Conclusion and future work

This paper identified the effectiveness and utility of combining a linear regression model with the MPNN. Although the methods presented in the paper includes a simple linear model, it is possible to substitute the linear model for any other justifiable analytic model such as simple Hidden Markov Model and etc. for an appropriate class of problem. Further research may be in combining a HMM with MPNN to approximate more complex HMM techniques such as Coupled Hidden Markov Model (CHMM) or Factorial Hidden Markov Models (FHMM).

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