

ROAD SIGN RECOGNITION USING AFFINE MOMENT INVARIANT

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ABSTRACT

Ability to recognise road signs in due time is an essential aspect of safe driving especially at night. Hence an auto road sign recognition system is a desirable add-on to a night vision system. This paper presents the use of affine moment invariants (AMIs) as the invariant feature vectors, and the multilayer perceptron (MLP) neural network as the pattern classifier, in developing a road sign recognition system. Six classes of road signs of different position, size and orientation, which were extracted from various near infra-red (NIR) road scenes, have been processed to validate the system. The first four simple AMIs, $I_1 - I_4$, were used for the image registration. The AMIs, which were computed from central moments, formed a feature vector that was invariant under the general affine transformation. These feature vectors were then fed into an MLP neural network for classification. The MLP used was trained with the quickprop algorithm (QA), a variation of the standard back-propagation (BPA) algorithm. Scaling and transformation of the feature vectors have reduced its dynamic range significantly towards improving the network convergence and performance. The trained and tested MLP was then validated with a set of feature vectors. This study has achieved a 100% successful classification rate using a limited validation set of road sign images.

Keywords: Road sign recognition, affine moment invariants (AMIs), multilayer perceptron (MLP), quickprop algorithm (QA).

1.0 INTRODUCTION

Ability to recognise road signs in due time are very important elements towards safe and efficient driving (Fang et al., 2004 and de la Escalera et al., 2003). Road signs are important elements for guiding, warning, and / or regulating the behaviours of drivers in order to make driving safer and convenient (Fang et al., 2004; Fang et al., 2003). Therefore, a system that can detect road signs ahead at all the possible orientations is certainly desirable, especially at night. Such a system would be a very useful add-on night vision system like the Jaguar Night Vision System (Rio, 1995). Research findings which have shown that more than 50% of accidents had happened at night even though traffic volume is much lower have put significant weight into the desirability of an effective night vision system. And, that has provided the additional motivation for this research work. This work aims to develop a road sign recognition system that is invariant to the general affine transformation which covers translation, rotation, scaling, reflection, and elongation and shear transformation (Liong, 1996). In other words we aim to extract invariant features of road signs in near infra-red (NIR) road scenes. Readers who are interested to know more about vision system incorporating visual sensing devices in general, and other driver assistance tasks should refer to Fang et al. (2004) and the references there-in.

As a car approaches a road sign, the road sign appears larger and larger, and finally, as it comes to the side of the car, it appears to be “squashed” or elongated when seen from the side of the windscreen, similar to those depicted in Figure 1. Road signs may also appear to be distorted or enlarged when approached from winding roads. A good road sign recognition system should be able to detect all these variations with ease and speed.

Affine moment invariants (AMIs) were chosen as the invariant features (Flusser and Suk; 1993Suk and Flusser, 2003). Their ability to represent affined deformed, and to approximate projective-deformed images, well suited our task (Flusser and Suk, 1994). Besides that, as only low order of AMIs are required for most recognition tasks, this means computation and recognition is definitely faster compared to other moment techniques (Teh and Chin, 1988). Furthermore, moment based descriptors are also ideal for use as neural network inputs.

The system developed uses only the first four simple AMIs, $I_1 - I_4$, for image registration. Feature vectors from the various classes of road signs were fed

into a multilayer perceptron (MLP) neural network for classification. The fact that the feature vector was just of dimension four makes the classification task much simpler and simple neural network models such as MLP are efficient for the task (Masters, 1993). The general structure and the principal components of the recognition system is shown in Figure 2.

The following sections will give more detailed descriptions of the AMIs features used, the road signs investigated, the neural network classifier developed and the classification results achieved.

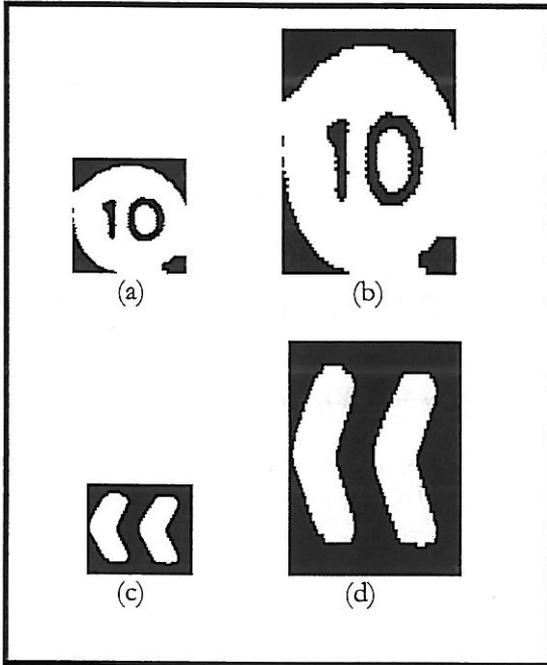


Fig. 1. Examples of the Squashing or Elongation Effect as the Road Signs Come Very Near:

- (a) The 10 mph speed sign at normal distance; (b) The squashed 10 mph sign;
- (c) The chevron sign at normal distance; and (d) the squashed chevron sign

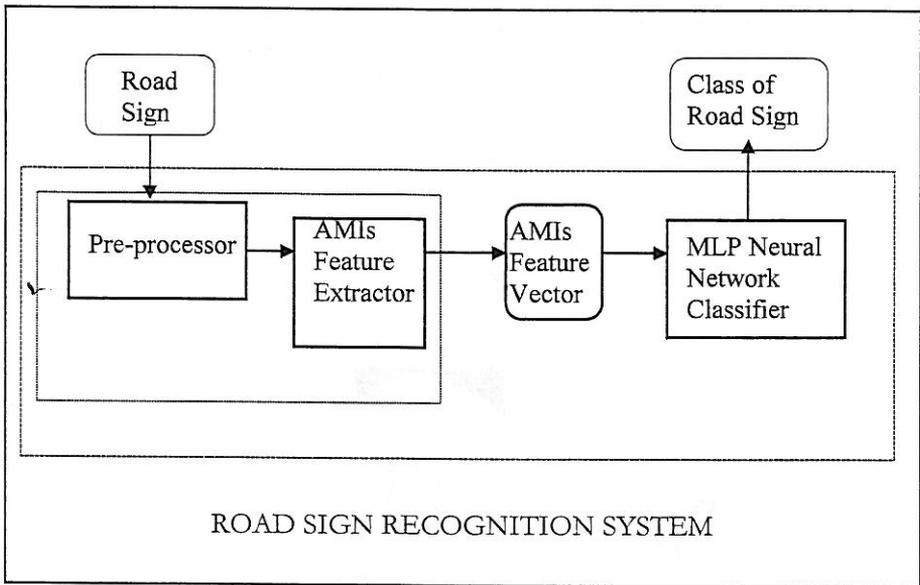


Fig. 2 The principal components of the road sign recognition system

2.0 AFFINE MOMENT INVARIANTS

Affine moment invariants (AMIs) are moments that are invariant under the general affine transformations defined by equation (1) below (Gibson 1988; Flusser and Suk 1993; Suk and Flusser, 2003):

$$\begin{aligned} u &= a_0 + a_1x + a_2y \\ v &= b_0 + b_1x + b_2y \end{aligned} \tag{1}$$

where (x,y) and (u,v) are the coordinates before and after the transformation.

An affine transformation can always be factored into the product of important special and simpler cases of transformations:

- a. translations: $u = x + a, v = y + b$
- b. rotations: $u = x \cos \theta + y \sin \theta,$
 $v = -x \sin \theta + y \cos \theta$
- c. stretching or shrinking (scaling): $u = tx, v = ty$

- d. reflections in the x -axis or y -axis: $u = x, v = -y$; or $u = -x, v = y$
- e. elongation or compression: $u = x, v = ty$; or $u = tx, v = y$
- f. simple shear transformations: $u = x + ty, v = y$; or $u = x, v = tx + y$

In other words, the general affine transformation covers translation, rotation, scaling, reflection, elongation and simple shear transformation. Please see references Gibson (1988), Flusser and Suk (1993), Suk and Flusser (2003), and Heikkilä (2004) for more details on affine transformation.

In the most general form, moments are defined using integral across continuous coordinates. Let $f(x,y)$ be the membership function of a continuous image, then the general two-dimensional moments of order $(p+q)$ for the two-dimensional density distribution function $f(x,y)$ are defined as :

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x, y) dx dy$$

For reasons of simplicity and speed, in this work we deal with just binary objects. Then the function f is simply a characteristic function of the object G , and the two-dimensional moments can be written as

$$m_{pq} = \iint_G x^p y^q dx dy \quad p, q = 0, 1, 2, \dots$$

If we use central moments (μ_{pq}) instead of the general moments (m_{pq}) given above, any function of them will be invariant under translations, i.e. one of the decomposed transformations of the general affine transformation. The central moments μ_{pq} of a two-dimensional continuous function $f(x,y)$ are defined as

$$\mu_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^p (y - \bar{y})^q f(x, y) dx dy \quad p, q = 0, 1, 2, \dots$$

where $\bar{x} = m_{10} / m_{00}$ and $\bar{y} = m_{01} / m_{00}$ are the coordinates of the centre of gravity of the object. For a digital image, the formula is simply

$$\mu_{pq} = \sum_{x=0}^M \sum_{y=0}^N (x - \bar{x})^p (y - \bar{y})^q f(x, y) \quad p, q = 0, 1, 2, \dots$$

And, from these central moments, by means of theory of algebraic invariants, the AMIs are derived. For the first four simple AMIs, they are composed of central moments up to only the third-order as shown below. This fact also means AMIs are relatively fast to compute and are less susceptible to noise (Teh and Chin, 1988). The first four AMIs, $I_1 - I_4$, which are reliable enough for most recognition tasks (Flusser and Suk, 1993), are given below:

$$I_1 = (\mu_{20}\mu_{02} - \mu_{11}^2) / \mu_{00}^4$$

$$I_2 = (\mu_{30}^2\mu_{03}^2 - 6\mu_{30}\mu_{21}\mu_{12}\mu_{03} + 4\mu_{30}^3\mu_{12}^3 + 4\mu_{12}^3\mu_{30} - 3\mu_{21}^2\mu_{12}^2) / \mu_{00}^{10}$$

$$I_3 = (\mu_{20}(\mu_{21}\mu_{03} - \mu_{12}^2) - \mu_{11}(\mu_{30}\mu_{03} - \mu_{21}\mu_{12}) + \mu_{02}(\mu_{30}\mu_{12} - \mu_{21}^2)) / \mu_{00}^7$$

$$\begin{aligned} I_4 = & (\mu_{20}^3\mu_{03}^2 - 6\mu_{20}^2\mu_{11}\mu_{12}\mu_{03} - 6\mu_{20}^2\mu_{02}\mu_{21}\mu_{03} \\ & + 9\mu_{20}^2\mu_{02}\mu_{12}^2 + 12\mu_{20}\mu_{11}^2\mu_{21}\mu_{03} \\ & + 6\mu_{20}\mu_{11}\mu_{02}\mu_{30}\mu_{03} - 18\mu_{20}\mu_{11}\mu_{02}\mu_{21}\mu_{12} \\ & - 8\mu_{11}^3\mu_{30}\mu_{03} - 6\mu_{20}\mu_{02}^2\mu_{30}\mu_{12} \\ & - 8\mu_{11}^3\mu_{30}\mu_{03} - 6\mu_{20}\mu_{02}^2\mu_{30}\mu_{12} \\ & + 9\mu_{20}\mu_{02}^2\mu_{21}^2 + 12\mu_{11}^2\mu_{02}\mu_{30}\mu_{12} \\ & - 6\mu_{11}\mu_{02}^2\mu_{30}\mu_{21} + \mu_{02}^3\mu_{30}^2) / \mu_{00}^{11} \end{aligned}$$

3.0 THE SYSTEM DEVELOPED

The main steps involved from the extraction of the road signs from the NIR road scenes to the generation of the AMIs feature vector basically are:

1. load the NIR road scene – to read the scene image
2. sub-image – to extract out the road sign portion
3. filtering – to remove noise
4. thresholding – to produce binary image
5. blurring – to smooth the image and make it more continuous
6. AMIs generation – to generate the AMIs feature vector

These are the main steps of the processing part of the system. However, since different road scenes will have different intensity and road signs at different positions or orientations, the following additional functions are provided to facilitate processing and locating the region of interest:

1. histogram of image
2. histogram equalisation
3. invert image
4. reset

For more detailed descriptions of the system please see (Liong, 1996). For technical information and discussion on the techniques mentioned above please see (Sonka et al., 1999; Gonzalez and Woods, 2002).

Once the image has been identified and pre-processed, it is ready for the AMIs feature vector extraction. This is performed by using one of the two methods available under the AMIs Generation Control Panel: (1) the Infinite Impulse Response (IIR) Filter Method, or (2) the Direct Method.

The primary tool used for the AMIs generation is the IIR Filter Method as this is the fast digital algorithm for moments computation (Budrikis and Hatamian, 1984). The Direct Method is mainly for verifying the accuracy of the results obtained by the IIR Method. The two algorithms differ only in the way the central moments, the main ingredient for the AMIs generation, are computed. The AMIs, $I_1 - I_4$, are computed based on the equations described in Section 2.0 above.

4.0 MULTILAYER PERCEPTRON

The multilayer perceptron (MLP) is arguably the most popular neural network model, especially for pattern classification tasks (Lisboa, 1992; Magoulas et al., 2004). MLP is a feed forward neural network with one or more hidden layers between the input and the output nodes. The in-between layers are called hidden layers because their outputs are not directly observable. These additional hidden layers contain hidden units that are not directly connected to both the input and output neurons. The model used has three layers: an input layer, an output layer and a hidden layer in between the two. Each unit in the hidden and output layer is like a perceptron unit, and that is why it is known as multilayer perceptron. However, these perceptrons are different in that their

threshold function is a sigmoidal (s-shaped) function (Annema, 1995; Duda et al., 2001).

Many neural network systems use some form of the back-propagation learning algorithm (BPA) (Rumelhart et al., 1986; Fahlman, 1989; Fry et al., 1991; Duda et al., 2001). However, BPA is too slow for many applications, and it also scales up poorly as tasks become larger and more complex. Hence the classification task is performed by using the quickprop algorithm (QA), a variation of the standard BPA (Fahlman, 1989). QA is the fruit of an empirical study of learning speed in simulated neural networks conducted by Scott E. Fahlman. It is a second-order-based method combined with heuristics which seems to give faster convergence in many cases (Bose and Liang, 1996; Duda et al., 2001).

The configuration of the MLP neural network used to solve the road signs classification problem is given in Figure 3. The input to the neural network is the feature vector of the road sign pattern which is comprised of the first four AMIs, $I_1 - I_4$. The neural network will then classify these feature vectors into one of the six possible classes of road sign investigated in this study. The threshold with margin criterion is used to decide which of the six output units is activated. The output node corresponds to the class of the current input road sign will have a high output, typically > 0.9 . Any output that is between the threshold margin of 0.4–0.6 is considered indeterminate, and anything < 0.4 as inactivated.

The number of input nodes corresponds to the number of invariant features used, i.e. 4, and the number of output nodes is equal to the number of classes of the road signs, which is 6. The only difficulty in using a neural network is determining the number of hidden nodes required and the best connection topology among the nodes (Bose and Liang, 1996; Duda et al., 2001).

One major characteristic of back-propagation classifier is its long training times. However, the other characteristic that it frequently needs many hidden nodes and connection weights does help. The network was started with a 12 hidden nodes configuration.

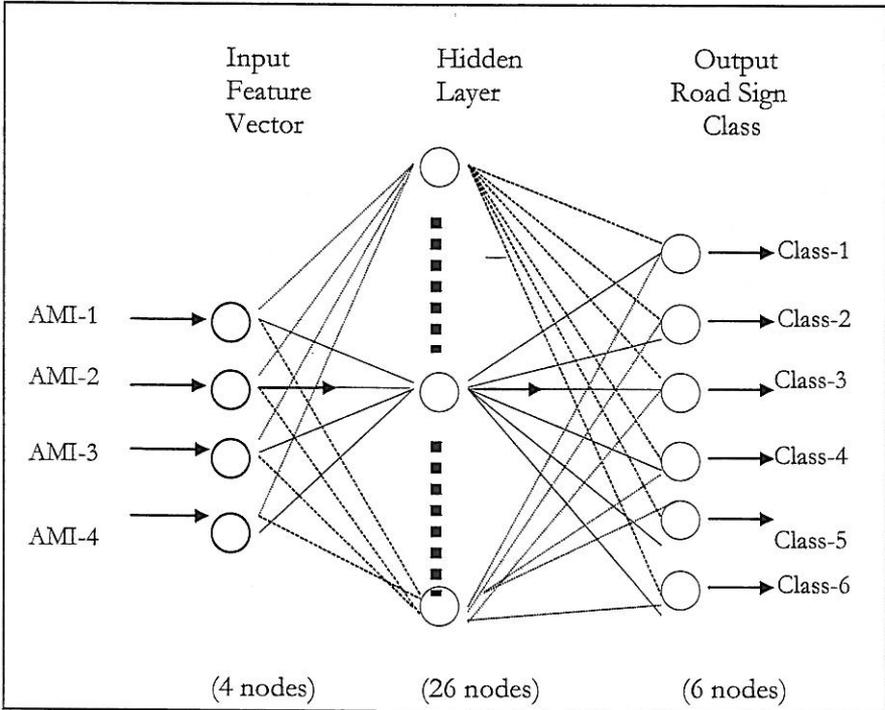


Fig. 3 The configuration of MLP neural network for the road signs classification system. To avoid notational clutter, most of the hidden nodes and the connection weights are not shown.

Fortunately, since the input feature vector is quite small (thanks to the virtue of AMIs), the network used is not that complicated. Increasing the hidden nodes from 12 to 18, 21, 24 and finally 26, and with variations in the QA parameters (the learning rate and the weight range), the best results were achieved. This final configuration performs 100% on a subset of the training samples; and almost as well with new patterns that it has not been shown before. It also managed to declare indeterminate a non-class input, i.e. input that belongs to none of the six classes.

4.1 Scaling and Transformation of Input

Scaling of the input and output range of a neural network is almost always recommended (Masters, 1993). Some neural network models, such as

Kohonen, have strict limits on their input values. For such a case, scaling is a must.

The output range for the MLP with the QA has been determined to be in the range of 0.0 to 1.0 by the unit type specified. It is the input feature vector that needs scaling or transformation. At the beginning, the network was tested with scaled down raw AMIs feature vectors. The scaling was done by simply dividing the feature vectors with the appropriate denominators to reduce its dynamic range. For example, the first AMIs were divided by 10^{-4} to reduce its dynamic range to hundred.

However, the dynamic range is still quite large for the network and it has a tough time to converge. The best performance obtained was just over 70% for the “unseen” validation patterns. The final scheme employed is to compress the data range by first taking the feature vectors cube roots, and then further scaling is done by dividing them with the appropriate denominator. This first step is a kind of transformation of the input operation. These transformed feature vectors show good success level. The AMIs calculated are explained in the sections below.

5.0 THE ROAD SIGNS INVESTIGATED

The samples of the various road signs tested are shown in Figure 5 where they are arranged by class. Six classes of road signs have been studied; and as many as possible road scenes have been analysed to obtain the road signs at different positions, orientation and scale. The road signs in Figure 4 below are shown in their original size and orientation. In the application, however, the AMIs feature vectors were arranged randomly when they were used to train the MLP neural network classifier.

Some of the images are clean, some are noisy and some are rather blur. These combination of patterns are important in order for the neural network to learn the various possibilities involved and to generalise. A total of 36 road scene images have been processed. The AMIs generated for the various road signs are listed in Table 1.

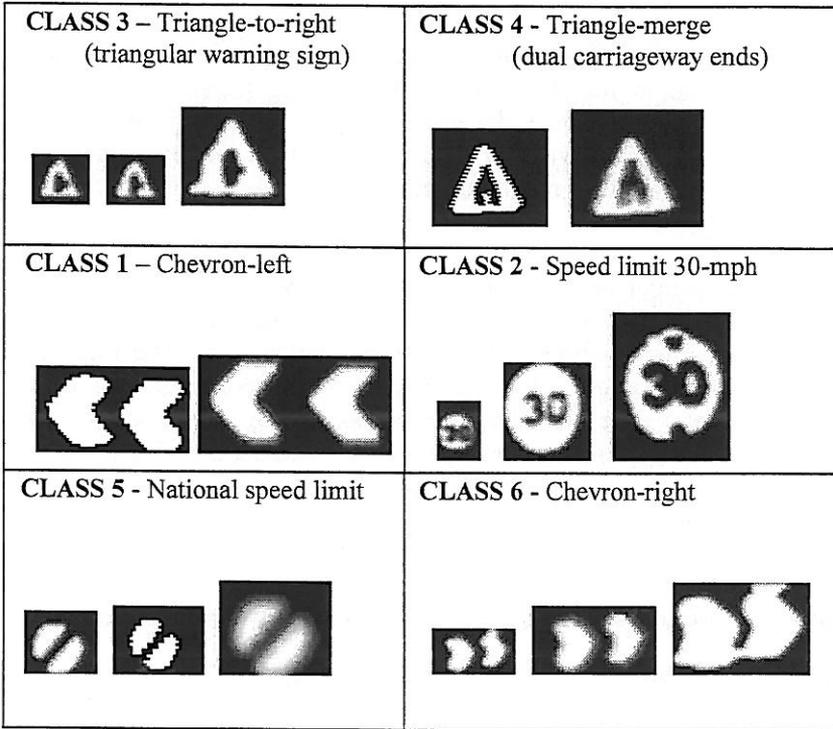


Fig. 4 Samples of the various road signs investigated.

6.0 TRAINING AND TESTING OF THE MLP

The scaled AMIs as shown in Table 1 were entered into the MLP neural network configuration file for training. They are entries to the input nodes. On the output side, the output node that corresponds to the class of the input pattern is set to 1. For example, the training patterns in the configuration file which belonged to Class 1 will have their first output node set to 1, and the rest to 0.

A large subset of the feature vectors representing the various classes were used to train the neural network using the QA. Each cycle through this training set is called an epoch. Training the MLP with the QA is quite a time consuming task in order to find the best configuration. Parameters like weight range and the learning rate, which are important for tuning (Fahlman, 1989; Duda et. al,

2001), have also been modified. A number of training phases have been carried out before the optimal configuration is achieved. A total of just over 60,600 epochs has been run in the 'most' successful training phase. Even though training was a slow process, once the network has learned the rules and the optimal connection weights have been set up, it performed the recognition task really quickly and well. In fact, it is an instance case for such a small collection of data on standard PC.

Training has been conducted until every output is correct for the test set, i.e. a 100% success rate. The test set was a subset of the training data patterns which were chosen randomly to observe the classifier performance. The threshold with margin criterion has been selected to decide the success criterion. For this case, any output that is over 0.6 will be regarded as a 1, any output below 0.4 as a 0, and any output between these two values as indeterminate. The test set is shown in Table 2, and the test results in Table 3. Since the node that corresponds to each of the expected class has an output > 0.9, which is well over 0.6, all the test patterns have been classified successfully.

Table 1. The transformed and scaled AMIs of the road signs.

Class	I'1	I'2	I'3	I'4
1	0.262514	0.476179	-1.075580	0.942734
	0.250269	0.967994	-1.369590	0.746044
	0.276079	1.580570	-1.281280	0.877011
	0.219184	-0.320659	-1.113560	0.507854
	0.212457	-1.164970	-1.415400	0.615262
	0.252289	0.686868	-1.714850	0.905071
	0.258863	1.045500	-1.251500	0.728596
2	0.209063	0.038126	-0.438855	0.188309
	0.202637	0.028192	-0.132009	0.074346
	0.203091	0.077275	-0.370005	0.158398
	0.185194	-0.056501	-0.405918	0.150359
	0.211015	0.065869	-0.414094	0.181594
	0.185113	0.030736	-0.405478	0.150122
3	0.201552	1.954570	-2.842410	1.146400
	0.201286	1.475000	-2.734390	1.101870
	0.212009	1.833440	-3.388960	1.437060
	0.210765	1.287620	-3.430880	1.446420
	0.214763	-2.174140	-3.536990	1.519340

(sambungan)

	0.214763	-2.174140	-3.536990	1.519340
4	0.199749	2.002040	-2.786470	1.113280
	0.271050	6.447410	-5.491940	2.978240
	0.200496	1.944310	-2.835570	1.137050
	0.198816	2.272400	-2.732240	1.086560
5	0.216141	-0.171501	-0.622428	0.269083
	0.196484	-0.175348	-0.597547	0.236413
	0.189882	0.171114	-1.029220	0.393504
	0.208277	-0.120437	-0.646782	0.276183
6	0.196491	-0.333237	-0.598640	0.284779
	0.193693	0.187995	-0.320819	0.149054
	0.218161	-0.338854	-0.960803	0.435507
	0.255616	1.047340	-1.556570	0.853078
	0.197284	-0.271905	-0.649735	0.297130
	0.208588	-0.085949	-0.465032	0.216539
	0.218021	-0.410203	-1.038510	0.466840
	0.239542	0.787544	-1.096130	0.586677
	0.246081	0.826840	-1.233650	0.663823
	0.249514	0.856433	-1.547700	0.818193

Table 2. The test set for the MLP neural network.

Number of Test Patterns 10									
----- Feature Vector -----				----- Expected Class -----					
I1	I2	I3	I4	1	2	3	4	5	6
#									
0.212457	-1.164970	-1.415400	0.615262	1.0	0.0	0.0	0.0	0.0	0.0
0.250269	0.967994	-1.369590	0.746044	1.0	0.0	0.0	0.0	0.0	0.0
0.218021	-0.410203	-1.038510	0.466840	0.0	0.0	0.0	0.0	0.0	1.0
0.239542	0.787544	-1.096130	0.586677	0.0	0.0	0.0	0.0	0.0	1.0
0.249514	0.856433	-1.547700	0.818193	0.0	0.0	0.0	0.0	0.0	1.0
0.212009	1.833440	-3.388960	1.437060	0.0	0.0	1.0	0.0	0.0	0.0
0.202637	0.028192	-0.132009	0.074346	0.0	1.0	0.0	0.0	0.0	0.0
0.199749	2.002040	-2.786470	1.113280	0.0	0.0	0.0	1.0	0.0	0.0
0.185113	0.030736	-0.405478	0.150122	0.0	1.0	0.0	0.0	0.0	0.0
0.189882	0.171114	-1.029220	0.393504	0.0	0.0	0.0	0.0	1.0	0.0

Table 3. The results of the test set. The activated output node is bold.

Pattern	Class Node					
Number	1	2	3	4	5	6
1	0.997376	0.000024	0.000271	0.000000	0.000000	0.001137
2	0.977140	0.000000	0.000009	0.000000	0.000001	0.044736
3	0.019860	0.000010	0.000000	0.000000	0.000021	0.978048
4	0.000014	0.000000	0.000000	0.000000	0.000041	0.992666
5	0.010253	0.000000	0.007046	0.000000	0.000005	0.979192
6	0.000004	0.000000	1.000000	0.000002	0.000026	0.000001
7	0.000003	0.999743	0.000000	0.000020	0.000000	0.000007
8	0.000001	0.000068	0.000002	0.999997	0.000016	0.000000
9	0.000000	0.999888	0.000000	0.000000	0.000502	0.000015
10	0.000000	0.000865	0.000000	0.000000	0.997695	0.005123

7.0 RESULTS AND CONCLUSIONS

The next step after the successful training session is to validate the neural network. A neural network system development is complete only when it has performed satisfactorily at this stage. Otherwise reconfiguration, retraining and validation have to be done. This cycle is repeated until the best configuration is attained.

The validation set which was comprised of “unseen” road images and two non-class patterns is shown in Table 4. The non-class patterns were included to observe the network behaviour on unrelated patterns. The two non-class patterns are the feature vectors for digitised letters *A* and *B*. The output obtained is given in Table 5.

Table 4. The validation set for the MLP neural network.

Number of Validation Patterns 10									
----- Feature Vector -----				----- Expected Class -----					
I1	I2	I3	I4	1	2	3	4	5	6
#									
0.218161	-0.338854	-0.960803	0.435507	0.0	0.0	0.0	0.0	0.0	1.0
0.196484	-0.175348	-0.597547	0.236413	0.0	0.0	0.0	0.0	1.0	0.0
0.203091	0.077275	-0.370005	0.158398	0.0	1.0	0.0	0.0	0.0	0.0
0.252289	0.686868	-1.714850	0.905071	1.0	0.0	0.0	0.0	0.0	0.0
0.198816	2.272400	-2.732240	1.086560	0.0	0.0	0.0	1.0	0.0	0.0
0.201286	1.475000	-2.734390	1.101870	0.0	0.0	1.0	0.0	0.0	0.0
0.255616	1.047340	-1.556570	0.853078	0.0	0.0	0.0	0.0	0.0	1.0
0.320753	3.914870	-5.104470	3.379580	0.0	0.0	0.0	0.0	0.0	0.0
0.306169	-1.786320	-2.519840	1.650960	0.0	0.0	0.0	0.0	0.0	0.0

Table 5. The results of the validation set. The activated output node is bold.

Pattern Number	----- Class Node -----					
	1	2	3	4	5	6
1	0.003922	0.000012	0.000000	0.000000	0.001845	0.937262
2	0.000004	0.000195	0.000000	0.000000	0.991835	0.006920
3	0.000000	0.999651	0.000000	0.000025	0.000149	0.000002
4	0.000052	0.000000	0.258214	0.000000	0.000004	0.991998
5	0.000002	0.000264	0.000000	1.000000	0.000045	0.000000
6	0.000032	0.000000	0.999999	0.000000	0.000376	0.000000
7	0.645157	0.000000	0.044682	0.000000	0.000000	0.003426
8	0.079165	0.000000	1.000000	0.000000	0.000000	0.000000
9	0.763243	0.000009	0.904289	0.000000	0.000000	0.000001

It is clear from the table that if we consider only the results for the road sign patterns, and the fact that Class 1 and Class 6 are interchangeable, the MLP has recognised all the road signs successfully, i.e. a 100% achievement. Class 1 and 6, the chevron-left and chevron-right signs, are symmetrical, and hence have the same sign under affine transformation.

It is also commendable that the MLP has managed to decide that the feature vector from the letter B is of non-class, where two output nodes, i.e. node 1

and node 3 have been activated. Since no class is associated with such an output, the result is considered as indeterminate and the pattern will be classified as unknown.

The only misclassification is the letter *A* which has been misclassified as belonging to Class 3 – Triangle-to-right. However, the guess is quite reasonable if compared to a contaminated Class 3's pattern. The fact that these two patterns are a little similar makes the results not too bad. Even if we take these two patterns into consideration, the overall performance of the MLP is still well over 88%.

From the results, it can be said that the AMIs and the MLP have shown promising results for the road sign recognition task that is invariant to position, size and orientation; or simply the general affine transformation. However, further research especially with larger set of images is essential before such a system can be considered for practical use.

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