Abstract – This article describes an on-line and real-time vehicle detection system. This system detects vehicles passing over magnetic sensors. It works independently of their initial position and of strong magnetic disturbance possibly induced by the load carried on the vehicles. This system is based on the co-operation between a reflective agent, using a reliability measure of its output, and a detection agent (on which this article mainly focus) based on two predictive neural networks and model selection techniques. The fusion of the data delivered by each agent is obtained through fuzzy logic rules. The system is also strengthened to resist substantial magnetic disturbances (even non-periodic ones); it uses the three components of the magnetic field, and is rotational invariant. Furthermore, its modular design opens up many possibilities of evolution.

Keywords: Fuzzy logic, predictive neural networks, data fusion, real-time detection, on-line detection.

1 - Introduction

In this article we partly describe a system based on the architecture previously introduced by F. Smieja in 1996 and modified by ourselves in 1998 (cf. [Sm96] and [Jo98]). We will mainly focus on three points. The first one is the introduction of predictive neural networks in the detection process. The second point is the adaptation of the fusion techniques to enable the system to manage these heterogeneous data. The last point is the comparison between the results obtained by the first system (presented in [Jo98]) and by the new one.

2 – Global architecture of the system

The architecture of the full vehicle detection system is pictured in figure 1. The main principles of this system are that the division in the input space is made at a symbolic level by the sub-tasks separation and the fusion is made with fuzzy rules.

At each sampling instant, the sensors give 3 measurements (one for each dimension of the magnetic field), and the information go through the entire system so that the detection decision can be estimated.

The results of the preprocessing operations are all independent of the terrestrial magnetic field. It is obvious that the geographical position of the measurement has some influence on the magnetic properties of the vehicle and consequently on the disturbance it generates (because of the induced part of it). The different parameters calculated during the preprocessing and used by the rest of the system are described in [Jo98], they are geometrical parameters such as norm, radius of curvature, angular displacement, etc. Furthermore, all of them are rotational invariant. As shown on figure 1, they are
both inputs of the different detection modules and context parameters for fusion and detection.

![Diagram](image)

Figure 1: general architecture of the system

The two detection agents are different and each one is dedicated to a particular subtask.

The first one is dedicated to the middle third of standard vehicles detection. It is composed of two predictive neural networks (Multi Layer Perceptrons) and a function of error estimation. It is on this module that we will focus our presentation (it is the major change of the system presented previously in [Jo98]). The main reason to change the first agent into a predictive neural network based one, is that, considering the results of the first system and the global approach we had, it seemed to us that the major inconvenient of our system was its lack of global temporal view. Compared to a classical classification neural network; a predictive one allowed us to take into account much more global temporal phenomena of the problem such as magnetic vector trajectory shape etc.

The second agent is detailed in [Jo98], it is dedicated to the non-standard vehicles approach detection (i.e. strong magnetic disturbances carriers). It is composed of a neural network (also a M.L.P.) trained with a specific detection function and an other M.L.P. which aim is to estimate the confidence that can be put on the output of the first one.

The fusion (also detailed in [Jo98]), and the detection decision are made with fuzzy logic rules based on the outputs of the two detection modules and some contextual parameters coming from the preprocessing. These parameters are also the inputs of the different neural networks of the two detection modules.

3 – First magnetic detection module: standard vehicles

For the standard vehicles detection, we used predictive neural networks. These networks modelize the magnetic field disturbances generated by a vehicle coming nearby the sensors. For this reason, we limited this approach to the standard vehicle detection problem. Actually, the non-standard vehicles have a priori not known characteristics as far as the close field magnetic disturbance is concerned. Consequently, a modeling approach for these vehicles seemed hopeless.

We did chose a solution with two neural networks. The first one is trained with samples of vehicles passing above the sensors, and the second one with samples of vehicles passing nearby. Both of them have been trained only with standard vehicles.

The discrimination principle between those two kind of passages is as follows: a passage to be classified is presented to each network, the class given to this passage will be the one of the network which has produced the weakest error. We obviously defined an ad hoc error criterion. The definition of this criterion (based on moving windows and cumulated errors) is also an original part of our work.

The parameters of such networks and those needed for the subsequent competition
fusion are difficult to estimate. We proceeded in three steps. During the first step, we designed the predictive neural networks for standard vehicles detection for off-line detection. This way, we reduced the problem to the detection of the standard vehicles middle third, knowing their complete signatures. This very hard restriction on the problem constraints allowed us to verify some of our hypotheses and to set some parameters of the system.

During the second step, we optimized the other parameters of the predictive neural networks considering the on-line detection problem. We have finally integrated the predictive neural network in the global detection system with suited fuzzy logic rules.

The predictive neural networks are used more to characterize the temporal shape of the different signals received by the sensors (to discriminate between the different kinds of passages) than to produce an excellent estimation of these signals. Nevertheless, we trained each neural network for prediction and their discrimination power obviously depends on the quality of their predictions.

The predictive neural networks that we used are Multi Layer Perceptrons. Their particularities is that the desired output they are trained with, is a future value of one of their inputs. The input we have chosen for prediction is the norm of the observed magnetic disturbance : this parameter seemed to be the most informative of all.

The learning base has been separated in two parts: an “over” part (with vehicles passing over the sensors) and an “aside” part (with the others). The “over” and “aside” passages have been presented respectively only to the “over” and “aside” network.

In our application, we must have “real-time” and “on-line” detection. Two major problems occur with on-line detection. First we have to find a way to discriminate in an efficient enough way the “aside” passages from the “over” passages so that this discrimination could happen before the middle third of the vehicle. Secondly, we have to detect the middle third of the vehicle in the same time.

Consequently, achieving this discrimination leads to define and then optimize a great deal of parameters. While the off-line discrimination is an easier problem, we preferred to test and tune some of our parameters on this problem. That showed us some limitations and possibilities of our approach. For these reasons, we designed an error analysis algorithm for the two predictive neural networks based on moving windows and weightings ; first we tested it on the off-line problem and then adapted it on the on-line processing.

4 – Competition principle : the moving windows

The error analysis for each neural network on a passage (in the off-line problem) is pictured in figure 2 and can be summarized like this :

During the first step, we stock the observed norm during the whole passage and the corresponding outputs of each network (i.e. the predicted values of this norm estimated by each network) on the same passage.

During the second step, we calculate the error of each network according to a certain number of delays and advances (these delays and advances are chosen close to the value that was set for the networks learning).

During the third and last step the class (“over” or “aside”) is decided to be the one of the network that made the less error in one of those cases.
In fact, the predictions of the networks are often very good (according to the shape of the predicted curve), but a certain offset (in time) often subsist. Because of this behavior, a single value of the network error is not representative enough of the network prediction quality. So, if we call $\tau_0$ the theoretical temporal delay between the observed norm $n_{\text{obs}}(t)$ and the predicted norm ($\tilde{n}_{\text{over}}(t)$ or $\tilde{n}_{\text{aside}}(t)$ depending on which predictive neural network is concerned), the relation we hope after learning is, in case of an aside passage:

$$n_{\text{obs}}(t + \tau_0) = \tilde{n}_{\text{aside}}(t) + \varepsilon_{\text{as}}(t)$$

and

$$n_{\text{obs}}(t + \tau_0) = \tilde{n}_{\text{over}}(t) + \varepsilon_{\text{ov}}(t)$$

with:

$$\varepsilon_{\text{as}} < \varepsilon_{\text{ov}}$$

But, due to this phenomenon of delay offset, we not only observe the difference between $\varepsilon_{\text{as}}$ and $\varepsilon_{\text{ov}}$, but between $\varepsilon_{\text{as}}(\tau)$ and $\varepsilon_{\text{ov}}(\tau)$, where $\tau$ is a variable close to $\tau_0$.

The value of $\tau_0$ was also a difficult parameter to choose. Its choice is fundamental for the system. There are two limitations for its value:

The upper limit is due to the delay that is consequently introduce for the final detection decision. Effectively, to calculate $\varepsilon_{\text{as}}$ and $\varepsilon_{\text{ov}}$, we need the value of $n_{\text{obs}}(t + \tau_0)$. Furthermore, the very beginning of each vehicle signature is the same and so, non-informative. If we assume $t_b$ the duration of the non-informative part of each signature, the total delay to wait to have significant values of the errors is $t_b + \tau_0$.

The lower limit for $\tau_0$ has two origins. Firstly, a very low value is impossible because of the sampling frequency used in the system and the need for a real-time system. Secondly, a low value means a short prediction horizon. If the prediction horizon is too short, the best prediction is quite always the linear prediction whatever the kind of passage. So the discrimination should become impossible (the two networks will make quite the same error).

5 – Weighting of the errors

After a brief analysis of the outputs of the predictive neural networks, it seemed that the overestimation errors should not be treated in the same way than the underestimation errors. There is a physical explanation to that observation:

The signatures of the “over” passages are, by nature, more “agitated” than the ones of the “aside” passages. In the three-dimension space, they present more direction changes and their norms are quite bigger.

Due to this matter of fact, the errors of the “over” network when facing an “aside” passage tend to be generally overestimation errors. In the opposite, the errors of the “aside” network, when facing an “over” passage, tend to be generally underestimation errors.

To take benefit from this behavior, we decided to take more into account the overestimation errors of the “over” network and the underestimation errors of the “aside” network. This is not a classical method for error processing in prediction, it comes from our need to better characterize the shape of the prediction compared to the shape of the observation rather than to seek a perfect prediction.

Formally, to take differently the
different errors into account, we used different weights to calculate the errors depending on their sign.

6 – On-line processing

The major problem of the on-line processing is that the total signature is not known when the detection should happen. So, assume that $t_c$ is the considered sampling instant, $\vec{B}(t)$ is the magnetic field vector, $n_{obs}(t)$ its norm, $\vec{n}_{aside}(t)$ the estimation of this norm made by the “aside” network and $n_{over}(t)$ is the estimation of $n_{obs}(t + \tau_0)$ made by the “over” network, we calculate the two error functions of respectively the “over” and “aside” network $E_{over}(\tau, t_c)$ and $E_{aside}(\tau, t_c)$ like this:

$$E_{over}(\tau, t_c) = \frac{1}{\min(t_c, t_f(\tau)) - t_0(\tau)} \sum_{j=t_0(\tau)}^{t_{\min}(\tau, t_f(\tau))} c_h \left| n_{obs}(t - \tau) - \vec{n}_{over}(t) \right|$$

$$E_{aside}(\tau, t_c) = \frac{1}{\min(t_c, t_f(\tau)) - t_0(\tau)} \sum_{j=t_0(\tau)}^{t_{\min}(\tau, t_f(\tau))} c_b \left| n_{obs}(t - \tau) - \vec{n}_{aside}(t) \right|$$

with

$$c_h = \alpha \quad \text{if} \quad n_{obs}(t - \tau) < \vec{n}_{over}(t), \quad 1 \quad \text{if not}$$

and

$$c_b = \beta \quad \text{if} \quad n_{obs}(t - \tau) > \vec{n}_{aside}(t), \quad 1 \quad \text{if not}$$

where $\alpha > 1$ and $\beta > 1$.

For each sample instant $t_c$, we chose the value of $\tau_v$ and $\tau_d$ which respectively give the smallest errors $E_{over}(\tau_v, t_c)$ and $E_{aside}(\tau_d, t_c)$. So, we obtain, for each network, a cumulated error, function of time, that we denote $E_{over}(t_c)$ and $E_{aside}(t_c)$.

While we have to take into account the temporal aspect of the signals, and not only the value at one instant, we define two functions $M_x(t_c)$ and $M_n(t_c)$. These functions depend on the cumulative sums of the difference between the two errors:

$$M_x(t_c) = \max_{t \in [t_0, t_c]} \left( \sum_{t=t_0}^{t_c} E_{aside}(t) - E_{over}(t) \right)$$

$$M_n(t_c) = \min_{t \in [t_0, t_c]} \left( \sum_{t=t_0}^{t_c} E_{aside}(t) - E_{over}(t) \right)$$

The detection can now simply be achieved with a couple of thresholds $(S_x, S_n)$ with the first order logic rule:

“The middle third of a standard vehicle is detected to pass over the sensors when $M_x(t_c) > S_x$ AND $M_n(t_c) < S_n$”.

In fact, these functions have not been used with first order logic rules but even like this, it is remarkable that the detection almost always occurs during the middle third of the vehicle. The explanation of this behavior is certainly the delay $\tau_0$, that prevent the system to detect anything too much early. Another influential point for this behavior is that the most informative part of the signature is roughly in the middle of the vehicle and the variance of the different vehicle speed is not very high.

7 – Fuzzy fusion

As the system still requires modularity and because we already made a fuzzy fusion module, the two functions $M_x$ and $M_n$ have not been used through first order logic rules but through fuzzy logic rules. The two functions are interpreted as possibilities value and one of the detection rule is: when $M_x$ is high enough and $M_n$ is low enough, then the passage of a standard vehicle middle third over the sensors is very possible.

Furthermore, we take into account the outputs of the other agent, which is specialized in non-standard vehicle and owns a self confidence estimation.

Working with fuzzy logic rules also
allowed us to work with symbolic contextual parameters in the same time. These parameters are a sort of contextual expert verification to prevent the system to do some very easily (with a little human expertise) avoidable mistakes.

8 – Results

The results are summarized in the following tables. They present the comparison of our new system (predictive neural networks) and the previous one (classical neural networks). These results are very satisfying in both cases because the average correct detection rate is over 80% for the standard vehicles. Moreover, as we noticed in the precedent section, the detection quite always occurs in the middle third of each vehicle.

These results have been obtained on a database containing approximately 500 vehicle signatures. We made a distinction for standard vehicles between “aside near” (when the vehicle passes closer than 50 cm to the sensors) and “aside far” passages for physical and industrial reasons. For “aside” passages, the good result is: no detection. The bad detection for the non-standard vehicles are detection that occurred not even under the vehicle.

The results of our new system are comparable to the first one. Contrary to the first system which is a little bit more efficient for “over” passages, the new one is better for “aside near” passages.

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<th>Table 1 : results for standard vehicles and over passages</th>
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<th>Table 5 : results for non-standard vehicles and aside passages</th>
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Concerning the quality of errors, the two systems share 75% of their errors. These 75% of common errors are made on either very near “aside” passages of big (magnetically speaking) vehicles or “over” passages of very light vehicles. This observation is in perfect agreement with the physic of the phenomena involved.

Concerning the possible evolutions of our system, we can try to optimize the architectures of the two predictive neural networks differently. For simplicity reasons, the current tests have been maid with networks of the same size. However, the modelization achieved by each network has certainly not the same complexity, so should certainly be the size of each one. Moreover, a more specific adaptation of the parameters of our fusion module is also to be done.

Furthermore, if we are able to use both systems at the same time, we can notice that 25 % of non common errors are a good potential for fusion of the two systems.

8 – References
