Automated Inferential Measurement System for Traffic Surveilance

Enhancing Situation Awareness of UAVs by Computational Intelligence

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Abstract— **An adaptive inferential measurement framework for control and automation systems has been proposed in the paper and tested on simulated traffic surveillance data. The use of the framework enables making inferences related to the presence of anomalies in the surveillance data with the help of statistical, computational and clustering analysis. Moreover, the performance of the ensemble of these tools can be dynamically tuned by a computational intelligence technique. The experimental results have demonstrated that the framework is generally applicable to various problem domains and reasonable performance is achieved in terms of inferential accuracy. Computational intelligence can also be effectively utilised for identifying the main contributing features in detecting anomalous data points within the surveillance data.**

Keywords*— *computational intelligence; inferential measurement; situation awareness; data anomalies; traffic surveillance; unmanned aerial vehicles

I. INTRODUCTION

Inferential measurement is a powerful and increasingly popular methodology that can enhance the operation of various sensor embedded systems through estimating difficult to measure characteristics by monitoring easily available parameters [1-4]. The information obtained through inferential measurements can be used to control and optimise the operation of these systems without the need to install a prohibitively large number of online sensors or to heavily rely on the accuracy and timeliness of the instrumentation data.

An unmanned aerial vehicle (UAV) can be considered an autonomous sensor system that is used to acquire large amount of data about complex and dynamic environments, to perform interpretation and fusion of the data, and to present the information gathered or inferred in a synthetic and compact form highlighting the features of interest in the environment explored. The situation awareness of a UAV is determined by its operating conditions, various inputs obtained from essential sensors, as well as control adjustments received from a ground station. The situation awareness is an example of a primary characteristic that is difficult to measure directly. However, the large amount of data coming from on-board sensors or received from a ground station can be referred to as secondary variables. Due to the nature of UAV operation, the states of many secondary variables reflect the states of primary characteristics. For instance, measurements obtained from the engine (torque, temperature, fuel compression ratio, etc.) can indicate, and even identify, faulty conditions affecting the operation of the entire UAV.

Heterogeneous data sources on-board the UAVs also add complexity in the form of analytical challenges, especially when there exists time and cost differences in processing data from different sources. Selecting suitable data acquisition sources, e.g. data that can be processed quickly in order to obtain representative samples, can help in time critical situations. Additional data acquisition sources that involve longer data processing but are more accurate or detailed, can be applied later to add a deeper focus on objects of interest identified in the representative samples. This process can also include logistical challenges such as controlling additional equipment to intensify data capture of a particular identified object of interest, e.g. a UAV can be sent to track a particular object of interest, and its camera on-board can be used to zoom in for more detailed images of this object; various on-board sensors can also be applied to obtain other relevant information so that inferences about the object of interest can be made and utilised.

With the vast amounts of data, traditional data acquisition and data processing methods have become inefficient or sometimes inappropriate, especially in a real time environment. Computational Intelligence (CI) techniques have been successfully applied to problems in various application domains [5, 6]. These techniques however require accurately labelled training data to provide reliable and accurate specification of the context in which a UAV operates. For example, drivers may behave differently in the different road conditions (e.g. icy, wet, and foggy). The term “driver(s)” used throughout this paper refers to drivers of vehicles on the road (i.e. in the simulated model) under the surveillance of a UAV and not the UAV’s controller. The context enables the system to highlight potential anomalies in the data so that intelligent and autonomous control of the underlying process can be carried out.

Anomalies are defined as incidences or occurrences, under a given circumstances or a set of assumptions, that are different from the expectance. By their nature, these incidences are rare and often not known in advance. This makes it difficult for the computational intelligence techniques to form an appropriate training dataset. Moreover, UAVs often operate in different or dynamic environments. This can further aggravate the lack of training data by the increased likelihood of intermittent anomalies. Computational intelligence techniques that are used to tackle dynamic problems should therefore be able to adapt to environmental/contextual changes.

In this paper, an inferential measurement framework for control and automation of systems on-board the UAVs with heterogeneous input sources has been developed and evaluated on a simulated traffic surveillance data. The framework is aimed at tackling problems in a real-time input data stream in dynamic problem environments, where the pattern(s) of interest (e.g. anomalies or faults) are relatively new and data related to them are limited or unknown. In order to achieve this, both statistical analysis and computational intelligence techniques are applied within the framework together with the online learning capability that allows for adaptive and autonomic problem solving. The framework has been successfully applied in the field of smart home environment as well as automotive process control [15]. This paper reports the evaluations on the applicability of the framework, on a different problem domain with minimal adjustments. The framework is used to evaluate the data obtained from the simulation: dynamically identify vehicles of interest; and classify these drivers based on their behavioural traits whether or not these drivers are anomalous.

II. Inferential Measurement Systems

Inferential measurement systems (IMS) aim to model the relationship between primary characteristics that are difficult to measure directly and secondary variables that can be more easily monitored. Although inferential measurements are widely used in industry, only a few techniques for inferential model development have been examined in detail. In general, three different types of approaches to building inferential models have been suggested: mechanistic modelling (based on first principles), statistical regression and artificial intelligence modelling [8].

Mechanistic modelling methods are based on the laws of physics and take the form of differential or algebraic equations. These methods perform well on the basis of a clear and good understanding of the mechanisms of the process, which is rarely attainable in practice.

Statistical regression methods overcome the need to gain full understanding of often non-linear, complex and uncertain behaviour of the process under investigation for building a usable inferential measurement system. Multivariate statistical methods such as principal component regression (PCR) and partial least squares or projection to latent structures (PLS) have been successfully used to build good inferential models. PCR and PLS are capable of including all relevant process measurements in a model without the problem of ‘‘overfitting’’ that is present in ordinary regression methods [8]. In this way all the process information can be included in the model leading to more accurate predictions.

Artificial Intelligence (AI) modelling has become a versatile tool for enhancing the capabilities and efficiency of inferential measurement systems. This type of modelling utilises the computational capabilities of modern computing devices (smart sensors, DSP-based microcontroller, and microprocessors) to effectively process the acquired input and infer the desired information. The AI-based techniques are applicable at various layers of IMS – from the data acquisition (sensor) layer, through to the layer of instrument calibration and customisation, then to the layer of process modelling, control and optimisation, and finally to the knowledge acquisition layer. The wide spectrum of possible applications is due to the capabilities of an IMS to gain insight into the behaviour of complex dynamic systems by means of data-driven modelling, a systematic approach to which is described next.

IMS are expected to work in one of the following modes of operation [9]. For processes with high degree of stationarity, an IMS with a fixed structure and static parameters of the inferential algorithms used is usually appropriate. For processes exhibiting frequent, but non-fundamental, changes, the ways how information is inferred needs to continuously adapt to these changes. Generally, this is achieved by having a fixed structure of an IMS, but the parameters of its inferential algorithms are required to be dynamically tuned in response to the changes. Finally, for the processes undergoing fundamental changes, evolving IMS might be necessary, which are capable of changing their structure as well as adapting the algorithms’ parameters.

In [6], the focus is on building and simulating an IMS of the second type, and an application of inference measurement in the context of anomaly detection in traffic surveillance. The current focus is on building and simulating an IMS of the third type that is capable of evolving its structure as well as adapting its parameters in the same context.

A. *Inferential Measurement Systems for Unmanned Aerial Systems*

The objective in developing inferential measurement systems is to model the relationship between primary characteristics and secondary variables. The model can then be used to generate estimates of the difficult to measure primary characteristics at the frequency at which secondary parameters are monitored. If sufficiently accurate, the inferred states of primary characteristics can then be used as feedback for automatic control and optimisation. Fig. 1 illustrates a generic framework for an IMS for a UAV, which is capable of enhancing the UAV’s situational awareness through real-time analysis of sensor inputs and evaluating relevant secondary variables. UAV encompasses both the UAV and other non-vehicle aerial system.

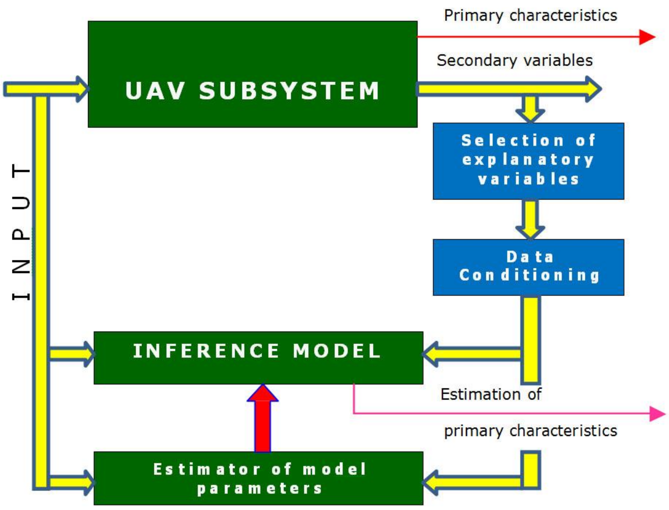

Fig. 1. A generic framework for an inferential measurement system for the unmanned aerial vehicle (UAV)

The idea for the inferential measurement systems, as shown in Fig. 1, is to mimic what experienced UAV operators and engineers would do in running the systems, but also be capable of alleviating the problems that lead to inconsistencies in human judgement. The procedure of building an inferential measurement system is based on developing a model that relates primary or high quality system characteristics to quantitative, and as such more easily measured, secondary variables. The ultimate goal of this framework to improve data gathering and processing activity in order to enhance the situation awareness to support real time decision making for the human operator on the ground.

However, identifying easily measurable parameters that determine the quality of primary characteristics (for instance, situation awareness) with sufficient accuracy are not trivial. If a manageable number of such parameters are identified, then the inference model can be built, given the acceptable quality of measured data. Moreover, an adaptive inferential measurement scheme can be adopted, whereby the inference model gets updated by dynamically tuning the model parameters. The next section discusses the adaptive inferential measurement scheme where model parameters as well as easily measurable parameters (i.e. secondary variables) are adaptively and automatically processed in real-time.

III. Processing Anomalies where the Pattern(s) of Interest is Unknown

The integration between computing processes and physical entities on-board the UAVs creates a dynamic problem environment of a network of interacting elements. Data about the real world environment can be transmitted to the computing processes within the system through monitoring and sensing; while inferences, which reflect policies of the system, are obtained by enabling the intelligent processing of these input data streams, and are used to autonomously control other computing processes or operate connected physical entities in the real world [10]. These interactions between computing processes and physical entities may results in changes in the quantity and quality of data being gathered and therefore dynamically alter the choices of resulting computing processes and operations of physical entities.

Computational intelligence techniques and expert systems have been successfully applied to tackling many anomaly detection problems where patterns of interest are known. Anomalies are rare and often incidences that are unexpected, and/or deviate excessively from the norm. Detecting anomalies with unknown pattern(s) of interest is even more complicated. Statistical analyses and clustering are examples of techniques that are commonly used to tackle such characterisations [11]. A systematic approach for the framework in Fig. 1 is developed, whereby statistical analysis and computational intelligence techniques are combined to autonomously identify suitable pattern(s) of interest for anomalies in the input data stream and learn from the experience when similar anomalies occur again. The approach is aimed at dealing with real-time systems that integrate a number of computing processes and physical entities. The logistical challenges of controlling physical entities is tackled in an ad-hoc basis, by executing required computing processes or activating necessary physical entities to obtain relevant data and processed required information when needed.

The input data sources to the system can be homogenous or heterogeneous sensors (e.g. ultrasound, thermal); or it can be computing processes (e.g. performing calculations, activating additional sensors); or even physical entities (e.g. changing the UAV's direction and manoeuvres it to achieve a better surveillance angle). The "Statistical Analysis" refers to STATISTICAL FUNCTIONS and *time windows*, for example, an AVERAGE (of data from an input source) *over the last 5 seconds*. The time windows can be continuous (e.g. time t0-t10, time t1-t11 and so on); or in consecutive but non-repetitive chunks (e.g. time t0-t10, time t11-t20 and so on); or in separation distances (e.g. t0 and t10; t1 and t11). A statistical analysis can also be nested, for example an AVERAGE of DIFFERENCE between two input values measured *at two different time steps with a separation time window of 10 in between the two measurements*.

During an inference process, one of the secondary variables can be an AVERAGE speed of the vehicle of interest *over the last 500 metres*. A tracking system may be used to measure the distance and calculate the vehicle's speed. The second secondary variable can be a DIFFERENCE of the distance between the vehicle of interest and the vehicle in front *from the previous measurement*. A different computing process and tracking system may be used to measure this distance. The third secondary variable may represent the TOTAL duration of tracking of this vehicle of interest *from the first time this vehicle appears* without applying any form of statistical analysis. These three light green squares in combination may represent a collection of statistical analyses applied to data gathered from different input sources that can be used to represent a pattern of interest (e.g. whether or not a data point is anomalous).

When the problem space is well defined or when there is a clear definition of the pattern(s) of interest, the decisions about which input sources and data streams to use; which statistical analyses are used to process these input data streams; and which computational intelligence techniques are used to identify the pattern(s) of interest, are in most cases, made by human experts through knowledge and experimentations.

In terms of data processing, the combination of statistical analyses and time windows can be viewed as adding different filters to input data streams. Processed data is passed to different learning techniques and used in different phases. This framework extends to include Classification and Prediction phases, where output from previous phases can be used in the later phases. For example, the abrupt change in lateral movement may cause the identification phase to identify a vehicle as a vehicle of interest. The classification phase may then attempt to classify whether or not this driver is anomalous (i.e. the cause of such changes is the driver's own behaviour) or normal (i.e. the cause of such changes is environmental, e.g. an obstruction) by evaluating and validating data from additional sources (e.g. road conditions). If the classification phase verified the anomaly and confirmed an obstruction, the prediction phase may simply switch off the alert for anomalous driver and send reports for the highway maintenance to clean up the debris. On the other hand, if the driver is anomalous, the UAVs may send the report to nearby highway police to stop the vehicle.

Fig. 2 illustrates an evolving and autonomous learning process for the systems when the problem space is not well defined by exploiting a meta-learning algorithm. In this case a Genetic Algorithm is used as the context-application controller that autonomously learns and makes decisions about these choices for techniques operating at the lower layers.

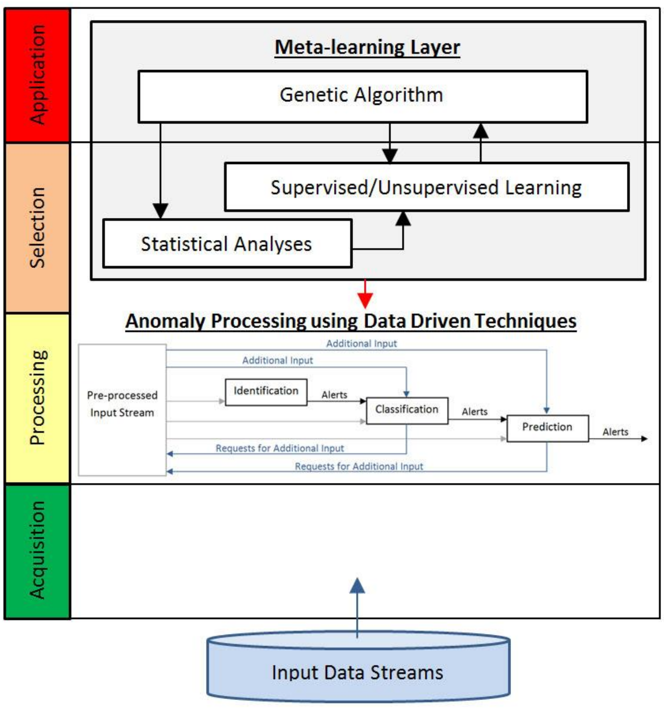

Fig. 2. A data-driven multi-tiered framework for evolving and autonomous learning systems by applying genetic algorithm

The framework in Fig. 2 spans a number of well-known and well-established disciplines that include machine learning, system identification, data mining, computational intelligence, signal processing, control theory and pattern recognition. The interconnections between computing processes and physical entities that must instantaneously exchange, parse and act upon heterogeneous data in a coordinated way, creates two major challenges: how best to process the amount of data available from various data sources that need to be processed at any given time and the choice of computing processes or physical entity configuration in response to the information obtained from the data collected and analysed. The systematic approach resides within the second and third layer (i.e. Processing and Selection layer) handles the challenges related to the volume of data, its veracity and velocity by optimising the balance between data availability and its quality.

The processing of the input data stream is segregated into identification, classification and prediction phases. The identification phase minimises the volume of data and the data processing cost by analysing only inputs from easy to process data sources using anomaly identification techniques such as outlier detection or statistical analyses. Identified potential anomalies are then passed onto the classification phase and classified into different types. At the end of the process, the prediction phase examines the consequences of the discovered anomalies being present in the operations of the underlying system.

Such an approach allows for the acquisition of data and/or activation of the necessary physical entities on an ad-hoc basis, depending on the outcome at each phase. Moreover, the accuracy attained at the specified phases can be enhanced by incorporating additional data from alternative sources.

The genetic algorithm, shown in Fig. 2, can be used to autonomously evolve system parameters (e.g. input sources to use, statistical analyses to process the data streams, supervised or unsupervised learning techniques to be used), a task which is generally carried out empirically by practitioners. The parameter optimisation can extend to encompass technique specific parameter settings. Using an artificial neural network as an example, typical examples of technique specific parameters are the number of input, hidden and output nodes in the artificial neural network, acceptable error rates, and stopping criteria.

After the meta-learning process has been carried out, the tuned learning technique(s) can be used to directly analyse the input data stream in order to provide the anomaly identification, classification, and ultimately prediction capabilities. If required, this tuning process can be carried out continuously and in near-real time.

IV. Experimental Results

The analysis of surveillance information in general, especially related to situation awareness, is a complex process that, given the amount and heterogeneous nature of data, is prone to data overload. This results in an inability to support real-time processing and analysis of surveillance data. This is especially true when using mobile platforms where datalink and bandwidth issues are significant [12, 13].

In this study, the data to be acquired and processed by an inferential measurement system comes from various sensors on-board a UAV, such as radar, electro-optical/infra-red, GPS and Inertial Navigation Systems (INS). Apart from on-board input data streams, additional contextual input data can also be taken into account. The choice of which contextual input to apply can be automatically tailored using the computational intelligence techniques. Fig. 3 illustrates an example of possible data sets that can be used during a surveillance mission. The complexity of the shown system increases with the number of additional dimensions of data.

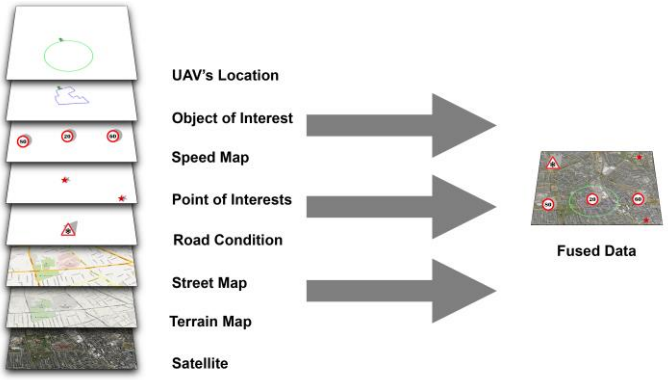

Fig. 3. Multiple data sources fused by an IMS

Therefore, a multi-tiered IMS that uses computational intelligence techniques should be able to enhance situation awareness of a UAV, especially in a real-time environment. Once anomalies are identified from fast data, additional data from both fast and detail-rich data sets can be added to improve the system classification and prediction performance.

The data-driven inferential measurement framework for control and automation of systems on-board the UAVs is implemented in JAVA and the Encog machine learning library [14]. Artificial Neural Network (ANN), Support Vector Machine (SVM), Bayesian Network (Bayes) are the computational intelligence techniques currently available in the framework, together with the K-Means clustering technique. Built in statistical analyses include Difference, Average, Variance, Standard deviation, Summation, Min and Max.

A traffic simulation is provided by Selex ES, a Finmeccanica Company. The model is developed using MATLAB. Anomalous drivers are defined as those that exhibit one of the two following behaviours: undertaking or overtaking without returning to its original lane. Normal drivers are defined as those that do not exhibit either of these two behaviours. Data that is provided by the simulation include: X and Y locations of each vehicle on the road and ground truth labels. The simulation simulates a total surveillance distance of a 6 kilometre road with three lanes.

A. Surveillance Distance

Due to the fact that anomalies are not always discrete events, but rather transitions between state types, a single data point is often insufficient to identify certain anomalies that necessitate making a time series of measurements. The longer the time series of data, the easier it is to identify such an anomaly. However, during a typical surveillance mission, a mobile surveillance platform covers an area with many different vehicles (e.g. traffic monitoring over the M1) and purports to provide better support the gathering of information such as accidents, stranded cars, or perhaps drunk drivers.

The amount of data related to each vehicle within the area would vary depending on the distance and angle between it and the surveillance platform, as well as on the travelling direction and speed of the vehicle. It is also possible that the visibility of the vehicle may be affected by weather conditions, terrain, buildings, etc. This set of experiments is designed to investigate the effect of sporadic coverage and how it effects the accuracy of the system in identifying anomalous drivers. Fig. 4 illustrates the effect of different surveillance distance on system accuracy rate between different computational intelligence and clustering techniques.

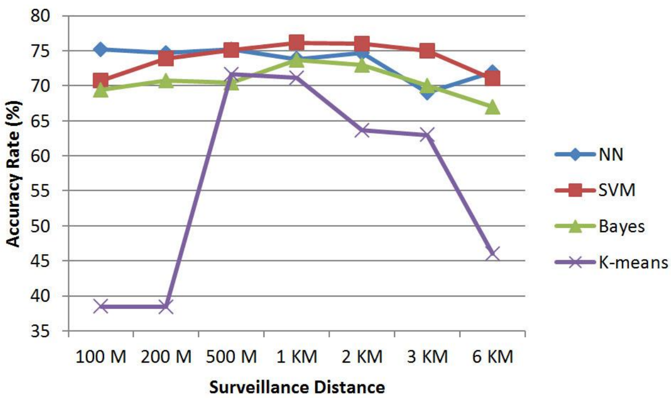

Fig. 4. The effect of different surveillance distances on system accuracy rate between different computational intelligence and clustering techniques

From Fig. 4, different learning techniques have different optimal surveillance distances. Artificial neural network and support vector machine approaches outperform other learning techniques in all evaluated surveillance distances. Fig. 5 illustrates the average accuracy rates between the supervised learning techniques (i.e. neural network, support vector machine and Bayesian network) and the unsupervised learning techniques (i.e. K-means).

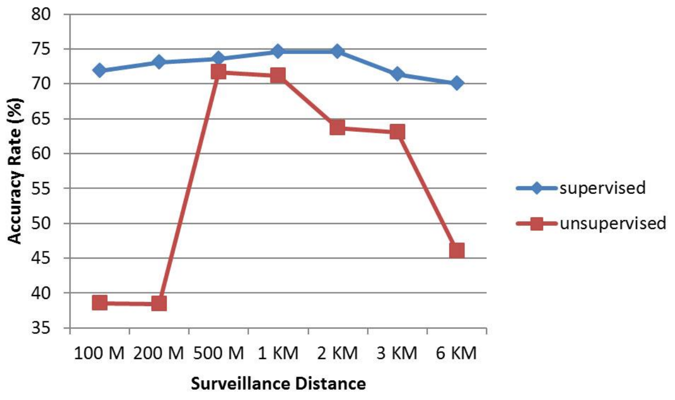

Fig. 5. The effect of different surveillance distances on system accuracy rate between supervised and unsupervised learning techniques

It can be seen from Fig. 5 that the accuracy rates of the supervised learning techniques are less affected by varying the surveillance distance. On the other hand, for the case of the unsupervised learning technique, a more optimal surveillance distance is required in order to achieve better accuracy rates. While the optimal surveillance distance of the supervised learning techniques are between 1 to 2 kilometres, the optimal surveillance distance for the unsupervised learning techniques are between 500 metres to 1 kilometre.

B. Number of Measurements

A genetic algorithm is used to optimise the combinations of statistical analyses, their time windows and supervised or unsupervised learning techniques. Fig. 6 illustrates the effect of varying the numbers of processed measurements used by the learning techniques. This set of experiments is carried out when the surveillance distance is equal to 1 kilometre.

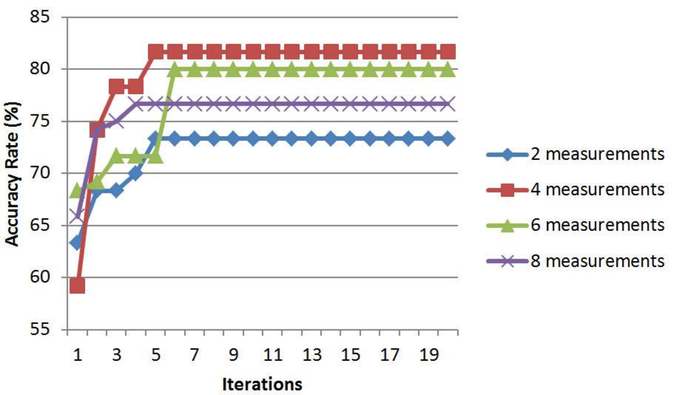

Fig. 6. The effect of different numbers of processed measurements on system accuracy rate on both the supervised and unsupervised learning techniques

From Fig. 6, four processed measurements appear to achieve the highest accuracy rate. This is made up of AVERAGE Lane, VARIANCE Lane, MAX Speed and STANDARD DEVIATION Speed. A support vector machine appears to be the best learning technique for all of these different numbers of processed measurements.

It was noted at least 50% of the chosen processed measurements are made up of different combinations of statistically processed Lane values. This shows that the genetic algorithm can infer the main feature that is used to specify the anomalous drivers. Table 1 summarises the identification accuracy rate after the genetic algorithm has evolved the population for 10 epochs.

TABLE I. IDENTIFICATION ACCURACY RATE (%) WHEN SUPPORT VECTOR MACHINE IS APPLIED USING DIFFERENT NUMBER OF PROCESSED MEASUREMENTS

# Measurements	**2**	**4**	**6**	**8**
Accuracy Rate (%)	73.33	81.67	80	76.67

During the experiments, after a couple of epochs, the genetic algorithm's population quickly converged toward support vector machine and therefore only the results from support vector machine are shown in Table 1. The identification accuracy rates reached their local optima after 6 epochs in all of the four cases of different number of processed measurements used.

C. Classification based on Different Bahavioural Traits

Once the anomalous drivers have been identified, the classification phase attempts to classify these drivers based on their behavioural traits. Currently, there are eight possible classifiable behavioural traits available; these are divided into two groups: dynamic and static. The dynamic group is made up of: slow, fast, wavey and dangerous. These behavioural traits are dynamic because they are calculated depending on the behaviour of other drivers on the road during surveillance. "Wavey" refers to when the driver zigzag between lanes more than the other drivers on the road while "dangerous" refers to the drivers that are both zigzaging and going a lot faster than the other drivers on the road. Fig. 7 illustrates an anomalous driver which was initially classified as a wavey driver but eventually classified as a dangerous driver when the vehicle is driven at a much faster speed than the other vehicles on the road.

Fig. 7. Anomalous driver being classified into different behavioural trait groups

The four static behavioural traits include: tailgate, undertake, bad safe distance and right hand lane hogger. These behavioural traits are static because they are classified using static thresholds or constraints. The tailgate and bad safe distance behaviours are classified using DVLA's 2-second rule; the undertake behaviour is specified as those that drive faster than the other drivers on its right hand lane; the right hand lane hogger behaviour is specified as those that overtake but do not return to its original lane when possible. On Fig. 7, the dynamic behaviour traits are tracked on the top part of the screen, while the static behavioural traits are tracked on the bottom half of the screen.

V. Conclusions

The developed adaptive inferential measurement framework for control and automation for the on-board UAV sensors is tested. Adaptability and autonomy of the framework are achieved through the combined use of statistical analyses and computational intelligence techniques. By selectively choosing a different number of inputs at the three phases of processing data (i.e. identification, classification and prediction), the processing of data in the input stream can be made more effective.

The experiments conducted on several datasets have demonstrated that reasonable performance can be achieved in terms of accuracy of data processing and its speed. The versatility of the proposed methodology is demonstrated by successful applications of the suggested framework to traffic surveillance, tracking a wall-following robot, environment monitoring in smart homes [15] and controlling the level of electromagnetic interference in motor vehicles [15]. Moreover, the performance of the proposed framework operating on shorter surveillance distances also looks promising, even with a surveillance distance of 100 metres, the supervised learning techniques still perform reasonably well.

In data-driven intelligent systems, input variables, the type of statistical measures used for pre-processing the input data, and the parameters of various computational intelligence techniques are usually obtained empirically. Another contribution of the work presented in this paper is the adaptation of a meta-learning procedure that is used to semi-automatically tune the set of input variables, the techniques to pre-process input data, and the salient features of the computational intelligence algorithms. These algorithms are then capable of identifying data patterns of interests that are used by the context-processing and context-selection layers of the multi-tiered framework. The meta-learning approach also showed potential for autonomously guiding the adaptive selection of the most effective salient features and parameter settings for the computational intelligence techniques. As shown in Table 1, an accuracy rate of 81.67% is achieved when a support vector machine is used to analyse four processed measurements.

The genetic algorithm guided inferential measurement system has shown to be generally applicable across a wide range of problem domains that require processing, analysis and interpretation of data obtained from heterogeneous resources. The fact that a meta-learning framework is able to correctly identify the main characteristics of anomalous driving behaviour is promising even when a simple fitness function is used. Further investigations will be directed towards improving the fitness function and extending the functionality of the system, improving its efficiency, and enhancing its scalability.

Acknowledgment

The authors would like to acknowledge the contribution of their industrial partner – Selex ES, a Finmeccanica Company – for providing the traffic simulation model, funding and general support for the work on this research project.

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