APPLICATION OF PREDICTIVE CONTROL MODEL IN AUTOMOTIVE SYSTEMS

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Introduction

In today's world, technology is skyrocketing to new heights and the automotive industry is not left behind. Intelligent vehicle systems are becoming an integral part of our everyday driving experience. They not only ensure safety but also make our driving experience more convenient and connected to the world around us.

In recent years, intelligent systems have become an integral part of modern cars, transforming the transport industry and improving safety and efficiency on the road. One of the leading technologies in this field is the application of Model Predictive Control (MPC) in automotive systems.

Model Predictive Control (MPC) is a control method based on using a mathematical model of a system to predict its future behaviour. In the context of automotive technology, this means using complex models to pre-calculate optimal control parameters based on current and future conditions.

MPC can analyse multiple variables such as speed, engine load, urban driving conditions and predict the optimal engine parameters to maximise fuel efficiency. This reduces fuel consumption and has an impact on the environmental sustainability of vehicles. MPC can be used to optimise the suspension and brake control system in real time. By taking into account vehicle dynamics and road conditions, the system can react quickly to changes, providing a more stable and comfortable driving experience.

By utilising MPC, cruise control can adapt to variable road topography and the movement of vehicles ahead. This improves safety and reduces driver stress.

In electric and hybrid vehicles, MPC is used to optimise the distribution of energy between the electric and conventional systems. This promotes maximum range on a single charge and increases the efficiency of the electric motors.

Efficiency: Predictive model-based control achieves optimal results, resulting in improved efficiency.

Reducing fuel consumption and improving the efficiency of transport systems results in resource savings. Adaptive control and pre-calculations allow systems to respond quickly to changing road conditions, which improves driving safety.

The application of the predictive control model in vehicles is a key step towards smarter, safer and more efficient vehicles. As technology advances, these systems will continue to play an important role in the future of the transport industry.

Electric and hybrid vehicles offer unique opportunities to apply model predictive control (MPC) to optimise efficiency, driving range and overall performance. Here are a few areas where MPC is proving its effectiveness:

MPC in electric and hybrid vehicles can optimise the energy distribution between different energy sources such as the electric motor, the battery and the internal combustion engine in hybrids. MPC algorithms take into account parameters such as the current battery charge level, energy consumption of different vehicle systems and even journey forecasts to determine the optimal energy distribution over time. MPC can also be applied to optimise the battery charging process. By taking into account time, energy cost, charging station availability and energy demand, the system can predict the optimum charging time and level to meet the driver's needs and minimise costs.

Using MPC, driving modes can be optimised based on driving conditions and driver tasks. For example, the system can predict when it is better to use the electric mode and when it is better to use the internal combustion engine to achieve optimal performance while minimising energy consumption.

MPC can control regenerative braking, which converts the vehicle's kinetic energy into electrical energy to charge the battery. MPC algorithms can predict changes in speed and braking requirements, optimising regeneration levels for maximum efficiency. MPC can also take route topography into account. Based on road gradient and other factors, the system can adapt its energy utilisation strategy to achieve optimal performance on hilly sections.

The application of MPC in electric and hybrid vehicles offers the opportunity to create more efficient and sustainable transport solutions, providing drivers with an optimal driving experience and extending journey lengths. It also contributes to the field of sustainable mobility, where transport solutions are integrated with environmental and energy considerations.

With the emergence of the first prototypes of robot cars, android robots adapted to work conditions impossible for humans, mobile robots - home assistants, robots to ensure the safety of unmanned aerial vehicles, underwater robots, etc., the concept of "robot" is also evolving. Contrary to the current situation, its semantic content is increasingly associated with industrial CNC machines, and it is increasingly correlated with artificial intelligence, which is capable of analysing incoming information, drawing conclusions and implementing behavioural strategies, as well as making optimal decisions in real time in conditions of extreme uncertainty in poorly structured environments.

In this regard, cognitive robots are distinguished, firstly, by an advanced onboard information and measurement system (IMS) containing an excessive number of often duplicating measurement channels, and secondly, by the mathematical apparatus used to process measurement information and implement various behavioural strategies based on the so-called probabilistic approach. Let us give an example of such an approach when solving the general problem of localising a mobile robot in an in deterministic environment.

The value $p(\vec{l}_k|\vec{l}_{k-1},\vec{u}_{k-1})$ is a motion model, representing the probability that the robot will be in position $\vec{l}_k$ if at time (*k*-1) it executes the controlling influence $\vec{u}_{k-1}$. In other words, a robot in position $\vec{l}_{k-1}$, can predict its new position $\vec{l}_k$ based on a certain action $\vec{u}_{k-1}$. In most cases, the control is time invariant, so the time reference number is often omitted.

The value $p(\vec{d}_k|\vec{l}_k)$ is the measurement model, which represents the probability that the on-board IMU of a mobile robot at position $\vec{l}_k$ will record the measurement data $\vec{d}_k$. Like the motion model, the measurement model is often time invariant, so the k index can be omitted. However, unlike the probability density of the motion model, the probability of the measurement model is difficult to compute.

The measurement information $\vec{d}_k$ of the on-board IMS is usually used to form a feature vector, which is then used to classify different behavioural strategies of a mobile robot. For example, the measurement data of a video sensor is an array of pixel brightness values of an image focused by an optical system on a light-sensitive matrix. By itself, this information is useless, but the extraction of object contours, pattern recognition in the image, and various geometric measurements in the image allow us to estimate the feature vector $\vec{d}_k = f(\vec{d}_k)$,, where f is the operator of transition from the space of all possible measurement results D to the feature space Z.

When forming a feature vector, the task of selecting the most informative features is to map the original n-dimensional space to a space of smaller dimension $m < n$ while maintaining the quality of separability of distributions corresponding to different classes. The function $v(\vec{l}_{k|k-1})$ has a maximum at the most likely location of the robot. Assume that the mobile robot has no information about its position after its initialisation, then the initial probability density $v(\vec{l}_0)$ will be uniform. Based on $v(\vec{l}_0)$, the robot calculates the control $\vec{u}_0$ and changes its position according to the transient probability density $p(\vec{l}_1|\vec{l}_0,\vec{u}_0)$. Then, at each time interval (k-1), the robot performs an action $\vec{u}_{k-1}$, which changes its position in accordance with the transient probability density $p(\vec{l}_k|\vec{l}_{k-1},\vec{u}_{k-1})$. In addition, it receives information by making relative and absolute measurements and extracts a feature vector $\vec{z} = f(\vec{d})$, which is distributed according to $p(\vec{d}_k|\vec{l}_k)$. The robot updates the degree of confidence in the information it has at each step k to obtain a better estimate of its real position $\vec{l}$. Then (1) the preliminary degree of confidence in the assessment of the position of the robot $\vec{l}_k$ before obtaining new measurement data at the k-th step and extracting the feature vector $\vec{z}_k$ from them, the degree of confidence in the assessment of the position of the robot $\vec{l}_k$ using the feature vector $\vec{z}_k$ is calculated by formula (2)

$$v(\vec{l}_{k|k-1}) = p\left(\vec{l}_k\middle|\vec{z}_1,\vec{u}_1,\vec{z}_2,\vec{u}_2,\dots,\vec{z}_{k-1},\vec{u}_{k-1}\right), \tag{1}$$

$$v(\vec{l}_{k|k}) = p\left(\vec{l}_k\middle|\vec{z}_1,\vec{u}_1,\vec{z}_2,\vec{u}_2,\dots,\vec{z}_{k-1},\vec{u}_{k-1},\vec{z}_k\right) \tag{2}$$

According to the theorem of total probability in integral form, the probability of an outcome is equal to the integral of the probabilities of its dependent private outcomes

$$v(\vec{l}_{k|k-1}) = \int_L p\left(\vec{l}_k\middle|\vec{z}_1,\vec{u}_1,\vec{z}_2,\vec{u}_2,\dots,\vec{z}_{k-1},\vec{u}_{k-1}\right)\cdot p\left(\vec{l}_{k-1}\middle|\vec{z}_1,\vec{u}_1,\vec{z}_2,\vec{u}_2,\dots,\vec{z}_{k-1},\vec{u}_{k-1}\right)d\vec{l}_{k-1} \tag{3}$$

This equation for the a priori confidence level of the position estimate *k l* is the integral of the probabilities of transition from position $\vec{l}_{k-1}$ to $\vec{l}_k$, taking into account all previously made measurements (4) multiplied by the probabilities of the robot being in position $\vec{l}_{k-1}$ for all available data up to and including the (*k-1*) -th step

$$p(\vec{l}_k | \vec{l}_{k-1}, \vec{z}_1, \vec{u}_1, \vec{z}_2, \vec{u}_2, \dots, \vec{z}_{k-1}, \vec{u}_{k-1}) \quad (4)$$

The development of cognitive robotics requires simultaneous improvement of the toolkit. It should better meet the needs of developers in terms of scalability, versatility, and a flexible modular approach to building mechatronic systems with an expanding set of configurations supported by each module separately.

Conclusion

Intelligent systems in cars are actively contributing to improved safety. Technologies such as collision avoidance systems, tyre pressure sensors, and rearview cameras significantly reduce the risk of accidents and provide extra pairs of eyes in blind spots. Intelligent systems are also stepping forward towards automated driving. These include cruise control management systems, auto parking, and even technologies that allow the car to adapt to the current road conditions. This not only reduces the driver's workload, but also improves driving efficiency. Modern car systems offer the opportunity to personalise the driving experience. Navigation, entertainment systems and even seat settings can be tailored to the preferences of the individual driver. This creates a unique and comfortable automotive experience for each owner.

In conclusion, intelligent systems in cars are an integral part of the modern automotive industry. They have made driving safer, more convenient and more connected to the world around us. Guiding the future, these technologies will continue to evolve, opening up new perspectives for car owners and shaping the face of the automotive industry in the years to come.

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