Information system of agricultural robotic KAMAZ cars

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Abstract. The article is devoted to the development of an information system for the complex of agricultural vehicles. It is shown that with the development of intelligent technologies, wireless communications, and the Internet, the task arises of creating a single information space for agricultural vehicles. The structure of sensors and measuring instruments installed on an unmanned KAMAZ car is described. The block diagram of the control system for the set of robotic cars is presented. The general structure of the information system, which includes a navigation system, technical vision, control units, a remote diagnostics subsystem, and a data transmission system, is considered. The technical diagnostics of the units is carried out using embedded and onboard thermal imagers. Thermograms from thermal imagers are analyzed using a convolutional neural network. Deep neural network and machine learning provided high accuracy in the detection and classification of equipment failures. The decision support system generates control signals for the units and transfers information to the highest level of control of the robotic complex.

1. Introduction
Robotic transport systems for various purposes perform many production functions [1]. The expansion of the scope of robots has reached agriculture. It is primarily due to the creation of robotic vehicles: combines, trucks, tractors [2, 3]. The complexity of the task of designing agricultural self-driving vehicles is due to the variety of external conditions in the fields, as well as difficult operating conditions. In this case it is necessary to create as the internal information system of the vehicle and to provide remote control and monitoring.

The first attempts for operating and controlling vehicles from a distance have started in the early 1900s, but systems of vehicle remote control started to be used widely in the 1970s [4]. The first tries for controlling robots via the World Wide Web had started in the middle of the 1990’s when the WWW started to expand all over the world.

The development of agricultural transport complexes involves the creation of information systems that form a single information space for controlling one or more unmanned vehicles or tractors [3, 5, 6].

2. Robotic system of agricultural vehicles with autonomous and remote control
The robotic system of agricultural vehicles based on the KAMAZ family of vehicles with autonomous and remote control (RSAV) is a human-machine system. The purpose of the system is to carry out
transport tasks by a robotic chassis, controlled by a dispatching control panel (DPU), which together forms a "robotic vehicle" (RV).

RSAV consists of the following subsystems:

- system of dispatching and management of the RV group;
- system of remote diagnostics;
- RV, including DPU and robotic chassis.

The robotic chassis is a technical device including the KAMAZ chassis, a motion control system, navigation systems, machine vision, measurements, actuators, and communications. RV sensors and measuring devices are shown in figure 1.

**Figure 1.** Sensors and measuring devices of the KAMAZ unmanned vehicle.

Functional RSAV implements the following features:

- Modeling of vehicle routes when performing transport and special tasks.
- Verification of simulated routes on a specialized software module to search for critical and bottlenecks.
- Assign tasks to operators of transport and special vehicles.
- Display on operator panels and digital forms of tasks assigned by the top-level dispatcher.
- Monitoring the implementation of assigned tasks by tracking the loading, movement, and downtime of vehicles and special vehicles.
- Collecting information on technical, operational, and other parameters of the functioning of vehicles.
- Analyzing of the vehicle park operation data to optimize performance.

The system is based on wireless technology and uses cloud data storage. The structural diagram of the RSAV is shown in figure 2. At the dispatch desk DPU RTS, a complex robotic RV is being controlled forming a unified robotic transport system (RTS).
3. Information system of supervisory control
The information system for robotic agricultural cars is a central part that provides functions:

- Motion control.
- Unit diagnostic.
- Data transfer to the operator.
- Data storage at different memory levels such as direct memory in the car, database, and cloud.

The block diagram of supervisory control is shown in figure 3.

4. Information subsystem for thermal imaging diagnostics of vehicle components
Non-destructive remote control methods should be used to monitor and diagnose the components of an unmanned vehicle. One of the most effective methods is the thermal imaging control of the temperature field of the object surface [8]. Using this approach, the authors have developed several intelligent diagnostic systems [10, 11]. They are based on a convolutional neural network [12].

For the diagnosis of autonomous cars, a subsystem for monitoring technical states was developed based on intelligent analysis of unit thermograms (figure 4). The subsystem includes an intelligent measuring system for classifying failures and a decision support system DSS.

Miniature embedded thermal imagers Optis PI400 measured the thermograms of the surface engine and transmission. A convolutional neural network in an intelligent measuring system is trained on complex model thermograms. Complex model thermograms are formed as

$$\theta_m = \{\Theta_m(x, y), V\},$$

where V is a vector of additionally measured object parameters and $\Theta_m(x, y)$ is solution of the two-dimensional heat transfer equation:

$$\frac{\partial}{\partial x} (\lambda(x, y) \frac{\partial T}{\partial x}) + \frac{\partial}{\partial y} (\lambda(x, y) \frac{\partial T}{\partial y}) + Q(x, y, t) -$$

$$- k(\alpha(T)(T - T_x) + \varepsilon \sigma(T^4 - T_x^4))) = \rho(x, y) c(x, y) \frac{\partial T}{\partial t}. \quad (1)$$
The following notation used in equation (1): $T$ and $T_S$ are respectively the temperature at the point $(x, y)$ and an ambient temperature; $Q(x, y, t)$ is power density of heat source; $\lambda(x, y)$ is a heat-transfer conductivity; $\rho$ and $c$ are respectively a density and specific heat capacity of the material; $\alpha(T)$ is a convective heat transfer coefficient; $\varepsilon_b$ is a coefficient of thermal radiation; $\sigma$ is the Stefan-Boltzmann constant; $t$ is a time of thermal process.

Figure 3. Supervisory control block diagram.

Figure 4. Monitoring engine and transmission by thermogram.

A trained neural network receives a measured thermogram and additional parameters of the object as an input and classifies the technical condition. A signal appears at the output of the neural network, showing the type of failure or defect corresponding to the measured thermogram. DSS generates control signals to the engine and transmission and sends information to the operator of the robotic car.
The use of deep learning of a multilayer convolutional neural network ensured the accuracy of the technical state classification for failures and defects of at least 97%.

5. Conclusion
In further research and development, it is advisable to improve the information system of robotic vehicles in the direction of using intelligent technologies for environmental analysis, real-time decision support, and quality management of agricultural work.

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