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Methods of Automatic Interpretation of Signals Used in Control Systems

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ABSTRACT

The article presents the concepts of control systems that use methods of automatic analysis and interpretation of signals. These issues are presented through the description of three control strategies: simple closed-loop control, control using a process of classification, and using a signal understanding technique. The systems based on the discussed concepts are illustrated with examples of controlling a milling machine and an autonomous vehicle. In addition, in more detail, a task of learning human motor activities is described. This task, due to the nature of the controlled object, which is a human being, is extremely difficult. The article shows that the advanced control process, in which the control algorithm is selected and its parameters are adapted to the current situation, may be implemented through the use of the classification process and machine learning methods in general. Changing the algorithm is also possible using signal understanding techniques. These techniques, utilizing models of the objects, allow to predict the long-term effects of the control process. The ability to build control systems that operate in the above manner is of huge practical importance. The aim of this article is to describe the methods of automatic signal interpretation used in control processes and identify the main problems related to their use. The key problems refer to the acquisition of expert knowledge by the system. In order for this knowledge to be effectively transferred, the methods used in the system should have a high level of explainability. Showing the essential nature of this feature is the main outcome of this work.

Keywords: pattern recognition, motor learning, automatic control, machine learning, image understanding, CNN network.

INTRODUCTION

The automatic analysis of signals can be understood very broadly. In a simplified form, this task involves processing the data provided by the sensors and determining values that characterize the controlled object. In classical control systems operating with feedback, these values are used to calculate the error signal used to correct the output value of the controlled object [1]. Despite its conceptual simplicity, the controller can operate on the basis of a sophisticated algorithm that takes into account a multidimensional error signal and outputs a multidimensional control signal. Examples of such devices are servo controllers (specifically in CNC machines), industrial robot controllers, and autopilot systems that control aircraft or surface ships. In many cases, the complexity of the controlled objects makes it necessary to use controllers that change their working algorithm. It depends on a set of variables describing the object and the phenomena in its surroundings. These variables should be subjected to a classification process [2, 3]. Its result points to the appropriate control algorithm in a given situation.

For example, a classification process can be implemented in a system that uses image analysis to check the quality of components being prepared for production. One of the specified classes may correspond to components of the right quality, while subsequent classes may refer to certain typical defects of the parts. Another example is the vision system used to control an autonomous vehicle, where classes have been defined corresponding to the different objects appearing in front of the camera. Yet another example is the use of the classification process in a telescope guiding system. By classifying the object seen by the telescope's camera into one of the prior defined classes, the appropriate guidance algorithm can be selected [4].

The third control concept discussed in the article derives from the fact that often, even with a very large number of classes, the result of the classification process does not sufficiently describe the variability of the analyzed phenomenon or object [5]. Controlling a complex object or group of them often requires creating its representation in a certain knowledge structure. This representation is called a model [6]. The process of creating a model of a particular object or signal and determining its meaning for the main (master) system is called automatic understanding [6] (this process will be defined more precisely in Section 4). The process of automatic signal understanding can be used, for example, in a vehicle control system in which the probability of collision with recognized objects is estimated on the basis of a physical model describing their movement in space. The main goal of this article is to describe the methods of automatic signal interpretation used in control processes and identify the main problems associated with their use.

Three approaches to signal analysis and interpretation will be discussed. They are used in three control methods outlined earlier, namely: simple closed-loop control, control using the classification process, and using the signal understanding technique. For each of the approaches, the following method of description is adopted. A general description is supplemented with three examples of its application. They concern the following tasks: milling machine control, controlling an autonomous vehicle, and carrying out teaching human motor activities. In cases of commonly known control methods or tasks, their descriptions have been limited to giving general concepts only. The third task, due to the nature of the controlled object (which is a human) is very complex. This will be described in more detail. In particular, the methods of signal classification used in its implementation will be presented. Additionally, an experiment will be described in which the effectiveness of the methods used is checked.

Between the example tasks described, there is a huge spectrum of tasks related to the control of manufacturing processes, transportation processes, and tasks related to supervision and monitoring. Proper interpretation of the signals involved in controlling these processes is therefore of great practical importance. For example, only advanced interpretation of motion signals allows the construction of systems designed to carry out the teaching human motor activities. The use of such systems in sports, rehabilitation, and teaching professional activities has undeniable social significance. The article is structured as follows: Sections 2–4 contain descriptions of three aforementioned concepts of control, Section 5 discusses the properties of the presented methods, and Section 6 summarizes the main conclusions of the study.

Simple feedback loop control

According to the general idea of working in a closed loop, the difference between the desired setpoint and the actual output value of the object is treated as an error signal. On its basis, using a specific algorithm (e.g., PID proportional-integral-derivative), the controller can bring the output of the object to the desired value [1].

Examples of closed-loop control processes

- Milling machine

An example of a closed-loop controller is a device that controls the movement of a milling cutter. It is moved between two defined node points at a preset speed. This speed is regulated by the PID controller.

- Autonomous vehicle

Another example of closed-loop operation is controlling the travel direction of an autonomous vehicle. A simple one-dimensional signal of direction can be obtained using a gyroscope and magnetometer (the direction of the Earth's magnetic field is used). However, this signal can also be calculated by analyzing the image of specific objects near the vehicle. An uncomplicated solution is to determine the position of a special line painted on the road. The calculated signal value is used to compute the error value used in vehicle control.

- System for human motor teaching

The third example we are considering involves an automatic system for teaching human motor activities [7]. The simplified diagram of the system is shown in Figure 1 [8, 9]. The object to be controlled is the learner. The input signals

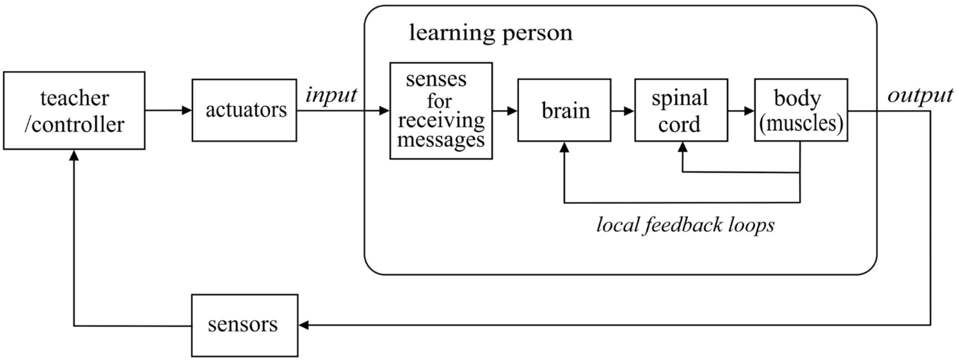

Figure 1. Diagram of the signal flow of the teaching system

of that object are the instructions of the teacher, whereas the output is the performed motor activities. The automatic controller, which plays the role of the teacher, assesses this activity and determines the means for its correction. Information about it in the form of special signals is transmitted to the object. It is extremely important that the information be provided quickly. Therefore, devices generating vibrotactile sensations should be used [9, 10, 11]. For example, the sensations can be generated by unbalanced mass DC motors, electrodynamic vibrators, etc. Due to their role in the discussed system, we will call these devices actuators. Motion acquisition can be implemented using many types of sensors. For example, MEMS (Micro-Electro-Mechanical Systems) devices, encoders, deflection sensors, vision systems, etc. can be used. The fundamental problem related to the operation of the discussed system is that the controlled object (the person being taught) is a non-linear, non-stationary object that uses its own algorithms to control the movement. Controlling such objects requires the use of advanced techniques, which are described in the following chapters. The use of relatively unsophisticated conceptual closed-loop control methods is only possible in simplified versions of the learning system. This simplification comes down to a significant reduction in the number of sensors and actuators. An example of such a system is the system intended for upper limb rehabilitation described in [10]. The other system that was created as a result of the master's thesis [12] works similarly (the author of the article was the supervisor of this thesis). Figure 2 illustrates its general view. The system uses only one sensor, which is an encoder that measures the angle, denoted by δ, between the arm and forearm. The described system works by checking whether the angle δ is within the given limits and whether the movement is conducted at the appropriate speed (the movement parameters are therefore angle δ

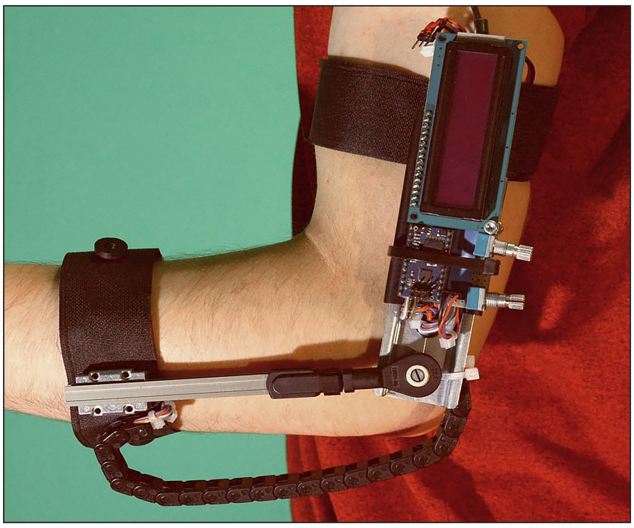

Figure 2. Simple system supporting the rehabilitation of the upper limb. The motion sensor is an encoder measuring the elbow joint angle, the system is equipped with Atmega 328 microcontroller and an actuator based on DC motors

and frequency of periodic motion). When the angle range is exceeded, vibration motors located in the band installed on the forearm are activated. The system created can be used in rehabilitation exercises. It can also be used by people after injuries for whom it is important not to exceed established ranges of movement in normal daily life (this application of the system was tested practically [12]).

In simple systems intended for rehabilitation, examples of which are given above, it is also possible to adaptively adjust the parameters of the taught movement to changes in the biophysical characteristics of the patient's body. For example, the system can aim to increase the frequency of the movement while maintaining a preset blood oxygen saturation level (the saturation is easily measured by transmission pulse oximetry).

Control processes carried out using classification methods

Unfortunately, changing the parameters of the algorithms is not enough to effectively control complex and non-stationary objects. As already indicated in Section 1, depending on the state of the object, the control algorithm should be changed. In order to select the appropriate algorithm, it is necessary to carry out the process of classification of signals characterizing the object.In general, the classification process consists in assigning to the object under study the class number (label) to which it belongs [2]. In our case, the result of the classification (i.e., the class label) points to the control algorithm to be executed. Let us outline the data processing steps that usually precede the classification process. Similarly to the simple control systems discussed earlier, the signals characterizing the object are read from the sensors and preprocessed (it consists, for example, in the filtration and normalization). In the next step, features of the signal are calculated. These can be parameters describing the signal (e.g., amplitude), as well as signal samples taken at discrete moments in time [8]. In the case of signals describing the image, the features are usually referred to the objects visible on it. The feature values form the feature vector, which is passed to the input of the classification algorithm. The described sequence of transformations is called signal or image recognition. It is illustrated in the Figure 3.

The signal resulting from a certain transformation can also be called an image. Therefore, the terms image and signal will be used interchangeably (the set of objects or the set of their feature vectors is also often called an image). Many classification methods are commonly used, for example: methods based on Artificial Neural Networks (ANNs), based on Support Vector Machine (SVM) [13], Hidden Markov Models (HMM) [14], minimum distance methods [3, 15], syntactic methods [2], and many other methods that utilize special solutions [16, 17]. In this study, we will briefly discuss only one of the minimum distance methods and a method using ANN.

Before that, let us try to answer the question: where does the classifier get its knowledge of what class number it should assign to the object under study? This question leads us to a more primary problem: how is the division of the set of all possible objects into classes made? This division includes knowledge of the properties of objects. An approximate form of this knowledge can be obtained from domain experts (experts in the field). For instance, in the case of the motor learning system, these are trainers, doctors, physiotherapists, etc. The expert defines certain classes by pointing to examples of objects belonging to them. Each example is a pair, containing a unique index of the object (or vector of its features) and the label of the class to which that object belongs. The set of examples is called a training sequence (also called a learning sequence or training set).

Let us return to classification methods. In the conceptually simplest method called NN (nearest neighbor) [2, 3], a distance function is defined in the space of feature vectors of objects (it is also possible to define functions describing the similarity between feature vectors). It evaluates how far

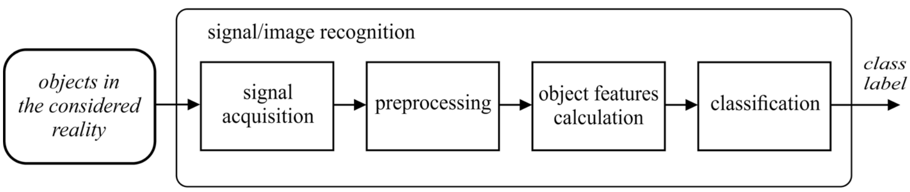

Figure 3. Stages of the image or signal recognition process

two feature vectors (characterizing two objects) are from each other. For each object in the training sequence, the value of the distance between its feature vector and the feature vector of the unknown, tested object is calculated. Then the element closest to the unknown object is selected. This element specifies the class of the examined object [2].

In tasks of classifying various types of data (time-varying waveforms, two-dimensional images, etc.), artificial neural networks are very often used [18, 19]. They are treated as automata with multidimensional input and output. The analyzed data (e.g., pixel values of the recognized image, quantized samples of a certain signal, etc.) are directed to the first layer of neurons. The neurons of the last layer derive values estimating the membership of the recognized image/signal to individual classes.

An essential problem with the use of ANNs is that a growth in the amount of input information (increasing the resolution of the analyzed image) leads to an increase in the number of neurons in the first and subsequent layers and the number of connections between them. This leads to a rapid increase in the number of parameters (synaptic weights) that need to be determined by training the network. With a large number of them, network learning algorithms become ineffective. The helpful solution is to consider not all possible connections between neurons but only connections in a limited local group of neurons. Simple transformations called convolution filters work in the manner described. The output value of the filter depends on the sum of products of the neuron values in the input of the filter and the corresponding parameters – elements of the transformation matrix [3, 19]. The calculated quantities are treated as the values of the neurons in the next layer. This layer is called a convolution layer.

Convolutional filters are defined using a very small number of parameters, but they can be used to detect features in the entire image. By combining subsequent convolutional layers, an image of features is obtained. It may be analyzed using MLP (Multilayer Perceptron) networks [20]. Convolutional neural networks (CNNs) and convolutional recurrent neural networks (CRNNs) [21], thanks to their effectiveness, have become common tools for solving classification tasks in many fields of technology but also in biology, medicine, and even in the humanities. This is also due to the availability of specialized multi-core microcomputers performing network operations (e.g., Jetson devices [22]). To summarize the current discussion, let us give a general scheme of the system in which the result of the classification process is used to determine the appropriate control algorithm [23]. This scheme is shown in Figure 4.

Examples of control processes that use the classification of objects

- Milling machine

Consider the movement of a cutter at a constant speed between two nodal points. During this time, the vibrations accompanying this process are classified. One of the defined classes is the class associated with the signals related to the tool wear phenomenon. If the vibration signal is classified into this class, the system executes an algorithm that brings the cutter to the second node point, but in such a way that the force acting on the tool is limited to a preset, safe value. This

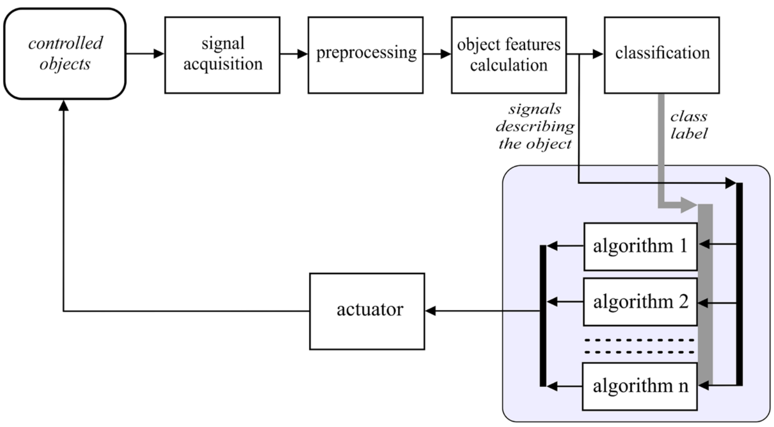

Figure 4. Selection of the optimal control algorithm as a result of the classification process

avoids stops between nodal points that result in large machining inaccuracies.

- Autonomous vehicle

In controlling the vehicle, in addition to maintaining its direction and speed, it is necessary to trigger reactions to events occurring in the vehicle's surroundings. Thus, in the driving task, the concept of using a classification process to recognize these events and then invoke the appropriate algorithms becomes obvious.

Assume that in the vision system used for vehicle control, the feature vectors describing objects include the following quantities: size, color, speed, and distance from the center of the road. The result of classifying the object seen in front of the vehicle determines whether a braking or evasive action should be triggered.

- System for human motor teaching

As an example of the use of the classification process in learning motor activities, the task of teaching a specific movement exercise during learning to swim the butterfly style will be presented. This task is described in detail in the author's work [8]. The exercise consists in moving the hands according to a given trajectory and timing.

The VN-100 MEMS [8], which contain 3-axis accelerometers and gyroscopes, are used as motion capture sensors. The movement performed is usually associated with small deviations from the preset trajectory, which are continuously corrected by a special teaching algorithm. The input of this algorithm is a multidimensional error signal calculated on the basis of the differences between the current movement and the given pattern trajectory.

This trajectory is determined on the basis of the so-called shape pattern [8]. This structure was created in the clustering process (part of which is averaging) of several dozen pattern signals collected from people performing the movement correctly.

The error vector is expressed in an inertial coordinate system related to the Earth. Using the operation of rotation, it can be expressed in the system related to the considered part of the body (signals from MEMS gyroscopes are used for calculations). This makes it possible to select the appropriate vibration actuator, which provides the student with information about the correct direction of movement. Unfortunately, during practice, there are often situations in which the student completely loses timing or makes very big mistakes. These situations are recognized (classified) by the system accordingly. Following this, a second algorithm is automatically invoked. This algorithm sends signals to actuators previously selected by an expert. The signals have a large amplitude and are intended to interrupt poorly performed exercises. The described algorithm restores proper synchronization of movements and prevents the acquisition of incorrect motor habits [8]. In the system minimum distance k-NNModel method is implemented [15]. It is an extension of the described NN method. For minimum distance methods, the key problem is how to define the distance function between the signals. Let us assume that a motion signal (e.g., position or acceleration) refers to a chosen coordinate of an individual sensor. A motion signal, denoted by S, may be represented by a sequence of probes: $S = (s^1, s^2, \ldots, s^n)$, where: s^k is the kth probe of the signal and n is the number of its probes. The S sequence will be called a one-dimensional signal. A function that compares two one-dimensional signals can be defined using a simple Euclidean metric:

$$r(P,S) = \left(\frac{1}{v}\sum_{k=0}^{v-1}(p^k - s^k)^2\right)^{\frac{1}{2}} \tag{1}$$

where: $P = (p^1, p^2, \ldots, p^m)$, $S = (s^1, s^2, \ldots, s^n)$ are one dimensional signals, m,n are numbers of their probes, respectively, and υ is the number of compared probes, $v \leq m,n$.

The result of motion signal classification should depend on the shape of the signal, not on its amplitude, speed, and the time shift between them. Let us introduce some auxiliary function $g(P,S,a,b,c,d)$, which returns the value of distance $r(P,S)$, however, after linear scaling and shifting of the P signal. The parameters a and b refer to the scaling and shifting of the signal indices (i.e., they relate to the time domain), whereas c and d correspond to the scaling and shifting of the signal values (a detailed description of these operations is contained in [8, 9]).

Using g function we can define a distance function between the signals

$$h(P,S) = \min_{\substack{a\in \mathrm{A}, b\in \mathrm{B},\\ c\in \mathrm{C}, d\in \mathrm{D}}} g(P,S,a,b,c,d) \tag{2}$$

where: A,B,C,D are sets in which optimal parameter values are searched.

The practical application of the described method depends on the existence of effective algorithms for calculating the minimum (2). The paper [9] presents a sufficiently fast heuristic algorithm.The function h evaluates the distance between one-dimensional signals. However, in the classification method used, multidimensional signals consisting of several one-dimensional signals are compared. For this purpose, a function is defined whose value is the weighted average of the h function values calculated on the basis of one-dimensional signals. The effectiveness of the described learning system was tested in an experiment involving 18 people [8]. They were divided into two groups. The first group was taught using only the algorithm for teaching movement along a given trajectory. For the second group, a classification process was used to select an optimal learning algorithm (an algorithm to prevent large trajectory errors was also used). Learning efficiency was evaluated with three quantitative parameters, denoted by E1*,* E2*,* and E3. The first parameter estimates the accuracy of the movement learned by the person (accuracy is measured by the RMSE coefficient calculated from an error signal of position) [8]. The second parameter is computed in a similar way, but it is calculated only in signal ranges in which the student does not make random erroneous movements. A classification process is used to determine these ranges. The third parameter estimates the effectiveness of learning. It depends on the values of E2 parameter calculated before and after learning. Calculating the average values of the parameters in each group of participants allows us to compare the effectiveness of the two teaching methods. For the group taught by one algorithm, the following parameter values were obtained: E1 = 95.4*,* E2 = 95.8*,* E3 = 70.3 (values are in millimeters). The results for the second group (in which the classification process was used) are as follows: E1 = 71.1*,* E2 = 69.1*,* E3 = 44.0 [8]. The results of the experiment were statistically analyzed using Student's T-test (twosample location test). Based on it, for all parameters: E1, E2, E3, with error probability: 0.049, 0.046, 0.042 respectively, we must reject the hypothesis that the effectiveness of both teaching methods is the same [8]. It should be assumed that the learning efficiency is higher for the method that uses the classification process. Similar results were obtained using the system for teaching movement synchronization [9].

Usage of signal/image understanding techniques

The output of the classification system is the label of the class to which the tested object belongs. This result is transferred to the master (main) system, which performs further actions, e.g., controlling the vehicle, conducting the patient's rehabilitation process, etc. However, there are some difficulties with this simple way (through the label) of representing the result of the interpretation process. In order to accurately determine the response of the master system, the number of object features must be increased. Consequently, each combination of feature values should be represented by a separate class (potentially, the number of classes goes to infinity [5, 23]). This leads to a rapid increase in the required number of elements in the learning sequence.

The subsystem that performs the interpretation should provide information about the meaning of the observed object (or phenomenon) for the master system. This meaning should make it possible to determine the reactions of the master system. In other words, the subsystem performing the analysis must provide a semantic value of the phenomenon being analyzed [24]. To do this, the subsystem must have knowledge of the observed phenomena (we will describe one form of this knowledge later).

The semantic value can be conveyed by contractual symbols or sentences in a certain language. For example, in the control system of an autonomous vehicle, the following semantic value may be derived: an object on the side of the road has been identified; do not start the braking procedure (e.g., due to the previously estimated low adhesion of the road surface and the low probability of a collision). Let us assume that we have a certain general knowledge structure in which information about the properties of the analyzed objects and the relationships between them can be represented. The representation of an exact object in the knowledge structure is called a model of the object [6]. Contrary to a simple description of the object, its model makes it possible to determine hidden object properties and its behavior. Finally, based on the model, we can determine its meaning for the processes taking place in the master system. Consequently, the semantic value of the object can be established.

The process of model creation, image understanding

Creating a model of a real object is a difficult task. It is necessary to transfer from a relatively easily determinable description of the real object (e.g., using its features) to an often abstract and symbolic representation of it in the knowledge structure. We will proceed in reverse order. First, some hypothetical model (i.e., hypothetical object representation) will be built in the considered knowledge structure. Then, in turn, a description of an object will be created, the representation of which would be this hypothetical model (the description of the hypothetical object can be given in the form of a feature vector). In the next step, the created description is compared with the description of the real object being analyzed. If these descriptions match, the hypothetical model is the representation of the real object under study. In other words, the model matches the real object. If not, the model should be modified and the match rechecked. In the strategy presented here, we start with some initial hypothesis determining the model of the unknown object (objects). Then, in subsequent iterations, this hypothesis is modified to obtain the best fit [6]. The model modification process is therefore performed in a closed loop. The presented way of creating a model and determining the output semantic value is called image (or object, signal) understanding [5, 6]. It is schematically depicted in the Figure 5. Despite the fact that new, advanced versions of the described methods are being developed, there is no complete agreement on what it means to understand an image or signal. It is most often assumed that the process of image or signal understanding contains cognitive mechanisms of information processing, including reasoning, searching the knowledge structure, its extension, and generating hypotheses [5, 6, 25]. Referring to this definition, let us specify the concept of image (signal) interpretation already used in this study. We will understand this term as a general process of creating an image representation in a certain knowledge structure and deriving its semantic value. However, we will not formulate any requirements (as in the case of image understanding) regarding the data structures used and the methods employed (e.g., the process can run in an open loop).

Using an ontological description

Knowledge about the examined objects can be stored in various data structures. The most common are graphs whose nodes refer to the components of the image and edges represent the relationships between them. Below, we will briefly present the knowledge structure in which certain generalized beings called concepts are utilized. The term concept is often referred to as class, category, or type [6, 16, 26]. It is assumed that there is a fundamental relationship between concepts

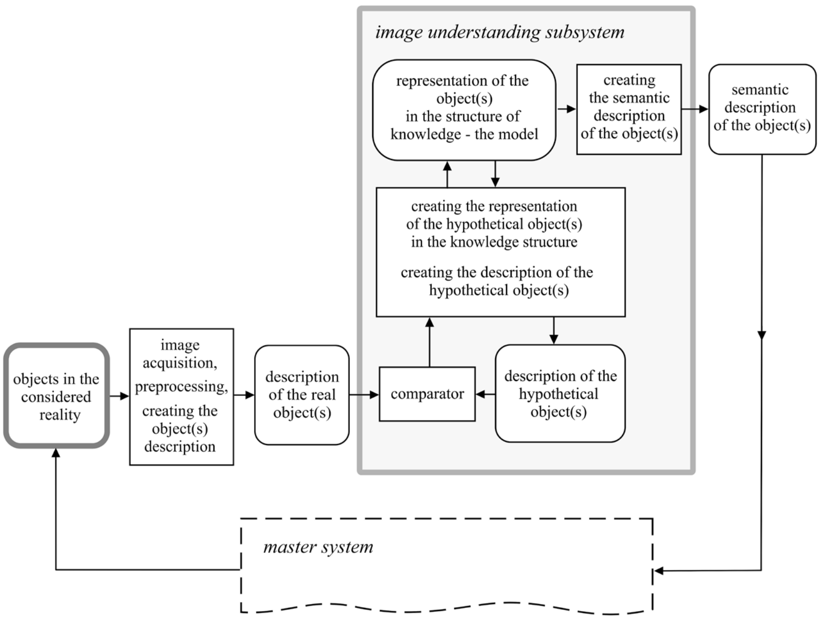

Figure 5. General scheme of the process of image understanding (objects and data structures are placed in the rounded rectangles)

and objects called membership. It is postulated that objects belonging to the same concept have similar properties. The set of defined concepts and relationships between them is the basis for the definition of the ontological model. It is also called domain ontology or, briefly, ontology [27, 28]. The strict definition of the ontology depends on the application domain and the formalism adopted [27, 29]. In a knowledge system defined using ontologies, operations on general and abstract forms of data can be clearly defined. The fact that an object belongs to a concept (class) implies that object transformations defined in a given class can be performed on it. It is also possible to predict the values of its selected features even when it is not possible to perceive them on the basis of the signals. However, building an ontological model is a complex task. It requires making some initial assumptions and defining a set of basic concepts and relationships. These activities require the significant involvement of experts.

In some situations, for relatively simple concept structures, the ontology creation process can be carried out automatically. The creation of an ontology model can then be based on the objects and relations between them observed in a given reality (learning by observation) [30]. For example, the structures of concepts (classes) can be automatically created in the inductive process of building the so-called micro-ontology [29, 31, 32]. In the ontological model, a certain semantic value can be assigned to objects and concepts. The determination of the resulting (overall) semantic value of an image is done through a process of inference. It may consist in the task of creating or finding a specific object or objects that belong to a certain concept. In this case, the semantic values of these specific objects determine the semantic value of the entire image.

Hybrid systems of signal recognition and understanding

The presented schemes for image recognition and understanding represent, despite their numerous variants, coherent ideas. However, modern applications often use intermediate solutions and those that only partially correspond to the types presented. In this context, the following tasks can be mentioned: understanding the functionality, events understanding [33], action/activity understanding [3, 33, 34], and semantic segmentation [6, 35] (it should be noted that the term understanding appearing in the presented list is used quite freely, including methods that do not correspond to the introduced concept of images understanding).

As a result of advanced analysis of signals/images, data structures are created that can be considered as an extended description of the control process. These can be used to build a semantic description of the controlled object and the entire control process. For example, in the processes preceding the classification of the movement performed by the rehabilitated person, the values of frequencies and amplitudes of motion are calculated. The moments of starting particular phases of movement of selected parts of the body are also calculated. Based on them, it is possible to derive commands that have semantic value regarding the correctness of the exercise.

Examples of control processes carried out with the help of signal understanding techniques

Signal and image understanding techniques are still under development. An example of an advanced, largely general system using ontological models is the CAREER [36] project (University of Michigan). However, the use of such systems for real-time control still faces many technical problems. In most cases, we can only consider the implemented systems as hybrid. The following examples illustrate this situation.

Milling machine

Suppose a vision system is used to analyze chips resulting from machining [37]. Based on the image of the chips, their features (e.g., thickness, curl radius) can be determined. They form a feature vector that can be classified. There are several basic classes of chips. If the chips belong to a certain class, selected chip features can be used to determine or adjust machining parameters such as speed and feed. These parameters are calculated using relatively uncomplicated mathematical models. The classification process is auxiliary. Its result is used to choose the proper method of modeling the machining process, not to select the appropriate control algorithm.

Autonomous vehicle

Let us assume that an image captured by the camera of the autonomous vehicle is preprocessed and segmented. This process involves separating consistent areas from the image that correspond to the basic, primitive objects. Each object is characterized by a feature vector, e.g., average brightness, size, color, elongation factor, etc. As a result of further data processing, objects are stored in an ontological structure. It contains not only feature vectors, but also information about classes of objects and relationships between them. The ontological structure also includes complex, compound objects. They consist of primitive objects that are connected by appropriate relations. The complex objects can form further compound objects, and so on [26, 29, 31]. Specifically, an object representing an animal (such as a horse) consists of a head, a torso, and legs properly positioned in relation to it. Suppose a particular object is represented in the ontological structure. There is also a previously created class of such objects. The class is accompanied by an attribute that allows to assess the probability of entering the roadway of an object (animal) belonging to this class. This value, along with the object's distance from the road and its speed, makes it possible to determine the semantic value. It may be as follows: start the braking process immediately .

System for human motor teaching

Automatic systems for learning motor activities in which a model of the analyzed phenomenon or object would be actively created, according to the author's knowledge, do not yet exist. However, there are systems that can be considered as hybrid [23]. The system described in [9] uses the classification process to select the learning algorithm and, at the same time, creates an extended description of the learning process. The information contained in it allows to derive results that can be considered as a semantic value. For example, the derived semantic values can be a simple command: increase the power in the first phase of the kick .

RESULTS AND DISCUSSION

The result of the classification process is a single decision variable (class label) that can be used to select the appropriate control algorithm. This solution is conceptually transparent and gives great possibilities for modifying the work of the entire system, including changing the temporary goal of the control.

Carrying out the classification process makes it possible to recognize and take into account the wide context of the system's operation and capture the key features of the controlled object. In the described solution, advanced, improved for decades, methods of signal analysis and classification can be applied. Effective methods of acquiring expert knowledge (e.g., based on a learning sequence) can also be used. The method of operation of the system presented above is one of the possible solutions. A more comprehensive description of the control process can be obtained by running several classification processes in parallel, each using a different criterion. The resulting set (vector) of decision variables can determine not only the algorithm performed but also the values of its parameters and even the output value controlling the object. An extended description of the control process can be used for a similar purpose. It is worth noting here that many methods usually used for classification are also able to determine the values of variables controlling the process. For example, a neural network can be trained in such a way that it directly outputs the value that controls the object [38]. An even more complete picture of the control process, along with a prediction of the object's behavior, can be obtained using its model and image understanding techniques. This makes it possible to construct control algorithms that achieve goals that are distant in time. Let us note here a possibility that is related in some way to the remark given earlier. A neural network capable of mapping any function can, of course, output a semantic value encoded in a certain way. The master system can use this value to control the object. An important problem is the acquisition of knowledge by the system.

In the methods using the classification process, this means the need to train the classifier using a learning sequence that is created with the participation of an expert in a given field. For the methods of automatic understanding of signals, it is necessary to build knowledge (e.g., in the form of an ontology) also with the participation of experts. In order for expert knowledge to be effectively transferred, the methods used in the system should be, at least to some extent, understandable by experts. Therefore, the methods should be characterized by the property of explainability (interpretability). In simplification, this term means the ability to provide a human-understandable explanation of the operation of

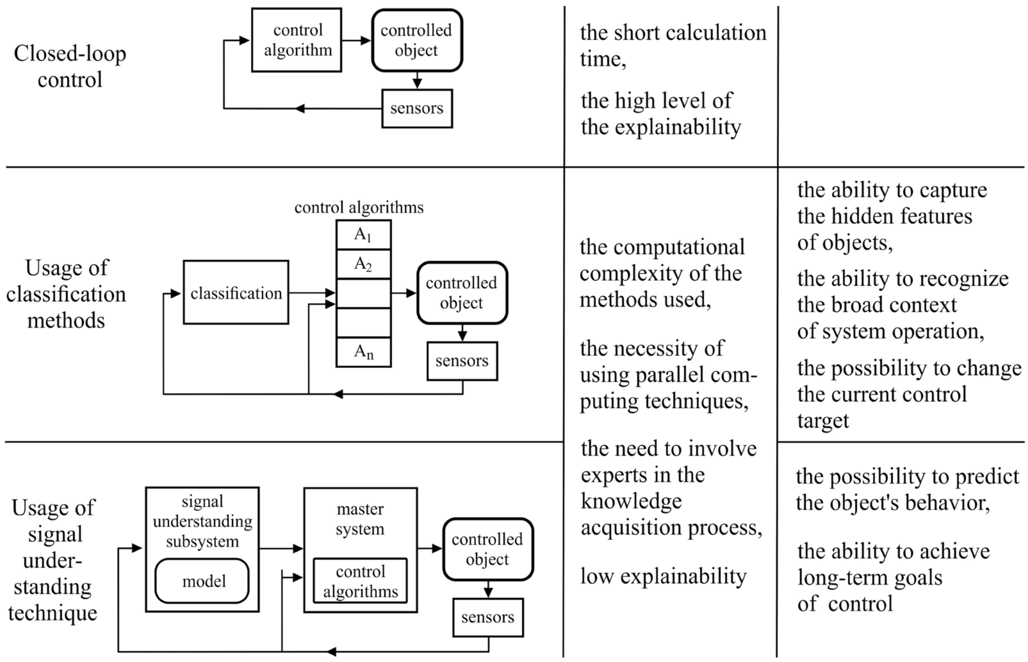

Figure 6. Main properties of three discussed control strategies

the method or system (there is a slight difference in the meaning of the terms explainability and interpretability, however, they are often used interchangeably) [39, 40].

Unfortunately, the explainability of most of the methods used to classify and build the structure of knowledge is low. In the case of neural networks, it should even be said that it is extremely low (network operation depends on thousands of synaptic weights). For this reason, many software tools are created that facilitate the interpretation of the network functioning (e.g., CNN Explainer [39]).

A summary of our considerations is illustrated in Figure 6. It shows very simplified diagrams of the approaches discussed and their main features.

CONCLUSIONS

In the article, apart from presenting examples of the classic approach to control, the concepts of using the classification process and techniques of signal understanding in the control process are described. The application of several control algorithms, selected in the process of classifying signals describing the object, makes it possible to change the goal of control depending on the current state of the object. The described method was successfully used in a difficult task of learning human motor activities. The selection of an algorithm or a change in the way it works can also be the result of the process of automatic signal understanding.

The use of a model describing the object and its surroundings also makes it possible to predict the long-term effects of the control. Consequently, distant goals of the control can be realized. The condition for the effective use of the described advanced signal interpretation techniques is the efficient acquisition of knowledge by the system. Knowledge is gained from experts, who should understand many aspects of the system's operation. Accordingly, the methods used should have the property of explainability.

Solving the problems identified in the paper is a certain challenge for the future. Particularly relevant in this context are:

- creating convenient software tools for building simplified domain ontologies used in control systems,
- development of specialized programs dedicated to control systems, explaining the operation of the applied methods of signal interpretation (similar to the CNN Explainer program).

REFERENCES

1. Dorf R., Bishop R. Modern Control Systems. Pearson Education Inc. 2011.
2. Tadeusiewicz R., Flasiński M. Rozpoznawanie

obrazów. PWN 1991.

3. Szeliski R. Computer Vision: Algorithms and Applications. 2nd ed, Springer Science 2021.
4. Wójcik K., Krzesiński J. Multi-task guiding system of the Mt. Suhora Observatory. Astronomy and Astrophysics 1993; 280.
5. Tadeusiewicz R. Automatic understanding of signals. intelligent information processing and web mining, Proceedings of the International IIS: IIPWM'04, Zakopane, Poland 2004; 577–590.
6. Sonka M., Hlavac V., Boyle R. Image Processing, Analysis and Machine Vision. Springer 1992.
7. Schmidt R., Lee T. Motor Learning and Performance: From Principles to Application. Human Kinetics 2019.
8. Wójcik K., Piekarczyk M. Machine learning methodology in a system applying the adaptive strategy for teaching human motions. Sensors 2020; 20: 314.
9. Wójcik K. Pattern recognition methods as a tool to build an automatic system for learning coordinated human motions. IEEE Access 2020; 8: 41407–41421.
10. Bark K., Hyman E., Tan F., Cha E., Jax S. Effects of Vibrotactile feedback on human learning of arm motions. IEEE Transactions on Neural Systems and Rehabilitation Engineering 2015; 10: 51–63.
11. Sigrist R., Rauter G., Riener R., Wolf P. Augmented visual auditory, haptic, and multimodal feedback in motor learning: A review. Psychonomic Bulletin & Review 2013; 20.
12. Wawrzyn D. Projekt i montaż aktuatorów urządzeń wspomagających czynności ruchowe człowieka. Master thesis, Cracow University of Technology 2018.
13. Taborri J., Palermo, E., Rossi S. Automatic detection of faults in race walking: A comparative analysis of machine-learning algorithms fed with inertial sensor data. Sensors 2019; 19, 1461.
14. Blasiak S., Rangwala H. A Hidden Markov Model Variant for Sequence Classification. IJCAI 2011, Proceedings of the 22nd International Joint Conference on Artificial Intelligence, Barcelona, Spain 2011; 1192–1197.
15. Guo G., Wang H., Bell D., Bi Y., Greer K. KNN model-based approach in classification. OTM Confederated International Conferences CoopIS, DOA, and ODBASE 2003, Catania, Italy 2003; 986–996.
16. Kulikowski J. Ontological models as tools for image content understanding. international conference on computer vision and graphics. ICCVG 2010, Lecture Notes in Computer Science, Warsaw, Poland 2011; 43–58.
17. Pałka D., Zachara M., Wójcik K. Evolutionary scanner of web application vulnerabilities. Computer Networks CN2016, Brunów, Poland 2016; 410–420.
18. Bishop C. Networks for Pattern Recognition. Oxford University Press 1995.
19. Zhang A., Lipton Z., Li M., Smola A. Dive into deep learning. release 0.16.1. https://d2l.ai. accessed on 2023.05.06, 2021
20. Krizhevsky A., Sutskever I., Hinton, G. ImageNet Classification with Deep Convolutional Neural Networks. https://proceedings.neurips.cc/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b- Paper.pdf accessed on 2023.05.06, 2013.
21. Munoz-Organero M., Powell L., Heller B., Harpin V. Using recurrent neural networks to compare movement patterns in ADHD and normally developing children based on acceleration signals from the wrist and ankle. Sensors 2019; 19.
22. Jetson embedded systems. https://www.nvidia.com/en-us/autonomous-machines/ embedded-systems/ accessed on 2023.05.06, 2023.
23. Wójcik K. Automatyczny System Nauki Czynności Motorycznych Człowieka. Monograph, Cracow University of Technology 2023.
24. Li P., Zhang D., Wulamu A., Liu X., Chen P. Semantic relation model and dataset for remote sensing scene understanding. ISPRS International Journal of Geo-Information 2021; 10.
25. Tadeusiewicz R. Automatic understanding of medical images (opening lecture). The 2nd International Conference Innovative Technologies in Biomedicine, PULMO-CAR, Cracow, Poland 2015; 10–11.
26. Wójcik K. Hierarchical knowledge structure applied to image analyzing system - possibilities of practical usage. International Conference on Availability, Reliability, and Security ARES 2011, Vienna, Austria 2011; 149–163.
27. Yaxin Y., Zhenhuan J., Xinhua L., Xutang Z. An intelligent approach for construction domain ontology. IEEE International Conference on Automation and Logistics, New Delhi, India 2009.
28. Ehrig M., Haase P., Hefke M., Stojanovic N. Similarity for ontologies. A comprehensive framework. Proceedings of Workshop on Ontology and Enterprise Modelling, Ingredients for Interoperability, in conjunction with 5th International Conference on Practical Aspects of Knowledge Management, Vienna, Austria 2004.
29. Wójcik K., Pałka D., Bar O. Micro-ontology building - main variants of OTO method. Technical transactions, Series: Electrical Engineering 2018; 115: 115–130.
30. Wójcik K. Observation as learning methods in Simple Visual System of Vehicle Control. Applied Mechanics and Materials 2014; 613: 144–150.
31. Wójcik K. Inductive learning methods in the simple image understanding system. International Conference on Computer Vision and Graphics. ICCVG 2010, Lecture Notes in Computer Science, Warsaw, Poland 2010; 97–104.

32. Wójcik K. OTO Model of Building of Structural Knowledge - Areas of Usage and Problems. Advances in Intelligent Systems and Computing, Image Processing and Communications Challenges 4 IP&C, Bydgoszcz, Poland 2012; 215–222.
33. de Souza F., Sarkar S., Cámara-Chávez G. Building semantic understanding beyond deep learning from sound and vision. 23rd International Conference on Pattern Recognition (ICPR) IEEE, Cancun, Mexico 2016; 2097–2102.
34. Tapaswi M., Kumar V., Laptev I. Long term spatio-temporal modeling for action detection. Computer Vision and Image Understanding 2021; 210.
35. Mayer C., Timofte R., Paul G. Towards closing the gap in weakly supervised semantic segmentation with DCNNs: Combining local and global models. Computer Vision and Image Understanding 2021; 208.
36. Corso J. Generalized Image Understanding with Probabilistic Ontologies and Dynamic Adaptive Graph Hierarchies. https://web.eecs.umich.edu/~jjcorso/r/career/index.html accessed on 2023.05.06 2020.
37. Hrechuk A., Bushlya V., M'Saoubi R., Ståhl J.E. Quantitative analysis of chip segmentation in machining using an automated image processing method. Procedia CIRP 2019; 82: 314–319.
38. Ku Ch.Ch., Lee Y. Diagonal recurrent neural networks for dynamic systems control. IEEE Transactions on Neural Networks 1995; 6: 144–156.
39. Guidotti R., Monreale A., Ruggieri S., Turini F. A survey of methods for explaining black box models. ACM Computing Surveys 2019; 51(5): 1–42.
40. CNN Explainer. https://poloclub.github.io/cnn-explainer/ accessed on 2023.05.06.