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Data Acquisition and digital Instrumentation Engineering Modelling for Intelligent Learning and Recognition

Jun Qin
Southern Illinois University Carbondale, jqin@siu.edu

Lin Xu

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Engineering Modelling of Data Acquisition and Digital Instrumentation for Intelligent Learning and Recognition

Jun Qin[1]* and Lin Xu[2]

[1]*Department of Electrical and Computer Engineering, Southern Illinois University, Carbondale, IL 62901, USA*
[2]*College of Computer and Control Engineering, Nankai University, Tianjin, China*

Abstract

In data acquisition and digital instrumentation fields, it is essential to understand the learning and recognition to acquire data and information of objects to be studied. In recent years, engineering modelling and simulation contribute greatly to the understanding of intelligent learning and recognition problems. The ability to learn is one of the central features of intelligence, which makes it an important concern for both cognitive psychology and artificial intelligence. In this paper, definitions and modelling aspects of learning are discussed. Fundamentals of learning and recognition and their applications are investigated and described. Illustrations are given to demonstrate the increasing applications of learning and recognition with engineering modelling in data acquisition and digital instrumentation fields.

Keywords: Data acquisition; Digital instrumentation; Learning; Recognition; Engineering; Modelling

Engineering Modelling and Learning

One important application of data acquisition and digital instrumentation is to realize the learning and recognition purposes [1]. The process of learning involves various communities and groups such as psychologists, philosophers, scientists of all sorts, and the parents of young children as well [2]. Precise definitions of learning are needed for engineers and scientists. Our interest in this field is motivated by a desire to make computers think like human beings. During the last a few decades, to learn to imitate a class of input/output behaviours has been attracting interests from both academia and industries. Different definitions of learning according to different reference and documents exist. According to Lesie Pack Kaelbing's explanation, learning means, roughly, a system's behaviour improvement by making it more appropriate for the environment in which the system is embedded [3]. The term "learning" has been used for various processes, such as "symbol-level learning" in which no information is achieved, but the internal processes are made to be more efficient. However, to give a solid computational definition of a restricted form of learning is not an easy issue. In common usage, "perception" typically refers to achieving information that is specific, transient, or at a low level if abstraction. The term "learning" typically refers to more general information that is true over longer time periods. Briefly speaking, any instance of the behaviour improvement through increased information about the environment can be termed as "learning". Research groups have been investigating the definitions and applications of learning [4]. Figure 1 shows diagram and modelling of a learning framework. In above framework, the objects or phantoms are to be investigated. Phantoms are widely used to mimic the real objects in many applications in industrial and clinical environments. In medical environments specifically, the phantoms can be tissue-mimic materials that have the similar physical or physiological properties of the real objects to be examined. The objects or phantoms are typically pre-processed before entering the recognition process in digital instrumentation designs for learning and recognition purposes. For classification or decision purposes, the output can be a single bit,

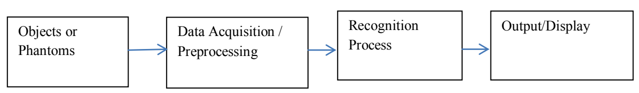

Figure 1: Figure shows diagram and modelling of a learning framework.

either 1 (if the case is recognized as belonging to a certain set), or 0 (if not). Sometimes, the output can also be displays to simply illustrate results in certain formats. Learning ability is essential for human intelligence. The learning ability enables us to adapt to the changing environment with developed various skills, and to acquire expertise in an almost unlimited number of specific domains [4]. Figure 2 shows the diagram of a typical learning framework with and ideal system to teach and compare to modify results. In Figure 2, the objects or phantoms go through the regular process to generate actual output/display, and go through the ideal system for output corrections as well. The actual and desired outputs are compared and feedbacks are sent to the learner. Rules or knowledge base will be modified to improve the system's performance to fulfil the learning task. One factor that influences learning is the degree of supervision. Sometimes, a tutor or domain expert exists to give the learner direct feedback about the appropriateness of its performance. This is the supervised learning. For unsupervised learning tasks, the feedback is absent. The supervised task

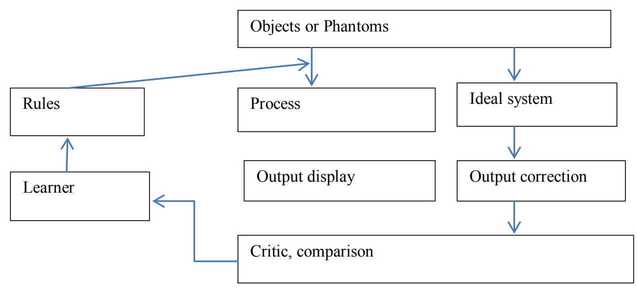

Figure 2: Learn system with ideal comparison.

***Corresponding author:** Jun Qin, Ph.D. Assistant Professor, Department of Electrical and Computer Engineering, Southern Illinois University Carbondale, Mail Code 6603, 1230 Lincoln Drive, Carbondale, IL 62901, USA, Tel: (618)453-3460; Fax: (618) 453-79, E-mail: jqin@siu.edu

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assumes that each training instance includes an attribute that specifies the class of that instance. The goal is to make a concept description that predicts this attribute correctly [5]. In problem-solving tasks, the supervised learning happens, when a tutor makes the correct step at each point in the search or reasoning process. Systems that run with such feedback are sometimes referred to as learning apprentices. However, most learn problems are based on unsupervised tasks without feedbacks. Therefore, the decision maker needs to distinguish desirable actions from undesirable ones on its own. This subtask is called the "credit assignment" problem. For those kinds of problems, the learner needs to make decisions responsible for success or failure of its problem-solving efforts. Once the learner has dealt with this issue, it can draw directly on supervised methods for classification learning to realize the tasks of problem-solving. Learning from examples or training sets is another basic learning strategy. This type of learning strategy is identified by viewing a learning system as an inference system. One can distinguish this type of learning strategy by the inference information with which the learning system (human or machine) performs, to derive the desired knowledge [4]. Several learning strategies exist. Here we list a few learning strategies shown as below. The direct implanting of knowledge learning strategy requires little or no inference on the part of the learner. The rote learning of memorization, learning by imitation, and learning by being constructed or by being programmed are involved in this strategy. Knowledge and information are incorporated into the system's hardware. Associated programs and databases will be generated for various applications in this strategy. The learning from instruction strategy is also called as "learning by being told". Knowledge and information are selected and transformed from the input language to an internally-usable representation by the learner. Those selected and transformed knowledge and information will then be integrated with prior knowledge to realize effective retrieval and usage. Another learning strategy is learning by analogy. It involves transformation or extension of current existing information in one domain to another domain with appropriate process. Compared with the learning from instruction strategy, this learning by analogy strategy requires more inference on the side of the learner. The learner needs to acquire relevant information or knowledge from the previous experience and transform those knowledge or information to be applied to the new environment to solve problems correctly. This is also a type of strategy of learning from examples. In this strategy, examples are given. Sometimes, counter-examples may also exist. The learner needs to induce a general description based on provided examples. For this type of strategy, the inference performed by the learner is greater than the inference in learning by analogy strategy. The learner has no prior knowledge and no knowledge from similar cases. The desired knowledge needs to be generated by making inductive inference from provided examples during the learning process. For data acquisition and digital instrumentation applications, learning is one of the important practical research directions. Therefore, learning strategies have been implemented in various applications of digital instrumentation to achieve the data acquisition and system development tasks.

Engineering Modelling and Recognition

Another important category in digital instrumentation with engineering modelling is to recognize objects. Recognition can solve problems related to many areas, such as non-destructive testing, production-line objects computer vision, medical diagnosis, language translation, and severe weather patterns [6-8], to name a few. Since the early1950's, when the digital computer became a potential tool to process information, the automatic recognition has begun to be developed rapidly and applied in various fields. The initial efforts of digital recognition included automatic decision-making, development of specialized hardware to read patterns such as printed alphanumeric characters [6], etc. In 1960's, as the computer technologies increased and the demand for faster and more effective communication between human and machine became important, research efforts on recognition system attracted great attention [6,7]. Since then, recognition techniques have been developed increasingly with a wide range of methodology. It covers no longer just the traditional statistical theories fields [9]. Rather, engineering modelling in recognition has become a major problem in the design of automated modern instrumentation systems. In this section, recognition and its applications in digital instrumentation fields will be discussed. A pattern represents the description of an object. As human being, one has the ability to organize and systematize patterns and pictures based on features and observations. Different objects can be observed and classified into specific categories based on their features and parameters. For objects with similarities, categories of overlaps may exist. The pattern can be essentially considered as an arrangement of an ordering in which some similarities or organization of underlying structure exist. The observations and recognitions actually happen in our ordinary lives and the entire world composes of features and patterns, to some extent. Watanable defines a pattern as an entity, vaguely defined, that could be given a name [10]. A pattern class can be viewed as a set of patterns that share some common properties. Certain given common attributes can determine the category of a pattern class. The objectives of recognition is to assign patterns to their respective pattern classes automatically and with minimum human intervention. In the past decades, recognition has been a very active field, particularly in the application area. The techniques have been used to recognize signals, voice, images, objects, fingerprints, and weather patterns, in many scientific, medical, and industrial fields. Generally speaking, recognition involves the partitioning or assignment of measurements, stimuli, or input patterns into meaningful categories [9]. One needs to extract the significant attributes of the data from the background of irrelevant details. Besides the common recognitions such as signal recognition, speech recognition, character recognition, etc., there are still many other applications of recognitions and verifications. For example, when we diagnose the patients, we use a variety of medical devices such as ultrasound instrument, the computed tomography system or radiography machines. A medical system that would accept the medical image to determine whether the specific zone on the input images was an abnormal or a normal area is a typical recognition system. Other applications include production-line vision and recognition of parameters of objects to be investigated, such as shapes, sizes, roundness, etc. Recognition by human beings may be considered as a psycho-physiological problem that involves interactions between a person and a physical stimulus [6]. We use our eyes, nose, and so on to perceive patterns. Human beings make an inductive inference and associates this perception with some general concepts or clues that people have already known from their past experience. One can logically divided the study of recognition problems into two main categories [6]:

1. The recognition study of human beings and other living organism. This recognition category involves the disciplines such as psychology, physiology, and biology.

2. The development of theory and techniques for the design of devices that are capable to realize given recognition tasks for specific applications. This deals primarily with engineering, computer, and information science. This category is also our focus in data acquisition and digital instrumentation fields.

The typical modelling components of a statistical recognition system with data acquisition are shown in (Figure 3). In Figure 3, objects or phantoms go through data acquisition and pre-processing, before the feature extraction process. The data acquisition part generally involves sensor technologies to detect various types of signals and information. The feature extraction part focuses on properties and parameters of the objects or phantoms to be studied. Features are determined based on tasks and are typically problems-oriented. For different design tasks, one can conclude different features for investigations. The classifier or decision is realized as the results of this recognition system.

Digital Instrumentation Applications

In digital instrumentation fields, learning and recognition are essential for the interpretation of acquired information of objects and phantoms [11]. For medical instrumentation applications, it is especially important to interpret the information or disease patterns to help decisions. For example, the typical steps in the learning and recognition for medical instrumentation applications can be shown as the following;

(1) data or information acquisition, for example, acquiring the computed radiography information with clinical machine, or acquiring the ultrasonic images by B-ultrasound devices;

(2) reduction and/or transformation of redundant and repetitive information stream;

(3) extraction of the most relevant features or parameters;

(4) classification of the patterns into one or more categories, especially useful for large dataset processing. It has become clear that digital instrumentation field is a very important and promising application for learning and recognition, including: presentation of information and patient profiles, selection of relevant features, information reduction and transformation with patterns stored in large database, etc. Besides the general industrial applications, a wide variety of instrumentation is available to the physician and surgeon to facilitate the diagnosis and treatment of diseases and other malfunctions of the body. Instrumentation has been developed to extend and improve the quality of life. A primary objective in the development of medical instrumentation is to obtain the required results with minimal invasion of the body. Responsibility for the design, implementation, installation, and maintenance of all medical instrumentations play essential roles in digital instrumentation design. The application of engineering principles and techniques has a significant impact on medical and clinical research aimed at finding cures for a large number of diseases, such as heart disease, cancer, etc., and at providing the medical community with increased knowledge [12]. Figure 4 shows our diagram of a generalized electrical instrumentation system [13]. In this system, sensor technology and signal processing are used to acquire and process information. The processed data sets are sent for displays and storages, and for further usage. The processed data sets are sent for displays and storages, and for further usage, such as communications for telemedicine, etc. Feedbacks are sent back to the effector as a part of learning and recognition for comparison and modification purposes, if needed. Learning and recognition can also be used in many different aspects in the field of data acquisition and electrical instrumentation. As another example, the science of biometrics provides an elegant solution of truly verifying the identity of the individual [14,15]. Biometrics systems can be viewed as a generic recognition system [16]. Features are extracted from the original signals for representation purposes. Then the matching and recognition subsystem can accept the query and reference templates and returns the degree of match or mismatch as results for final decisions [17]. In addition, using recognition techniques, different advanced algorithms can be adapted to reach high accuracy and fast speed detection. Using robust estimation of intensity, we can realize the adaptive filtering and segmentation to deduce different types of noise presenting in information as well as to enhance the data quality of studied objects. The recent developments of those technologies are helpful for a few applications such as non-destructive testing and clinical diagnostics [18].

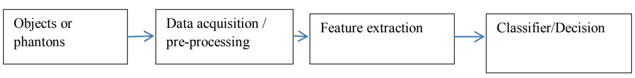

Figure 3: Modelling components of recognition system with data acquisition.

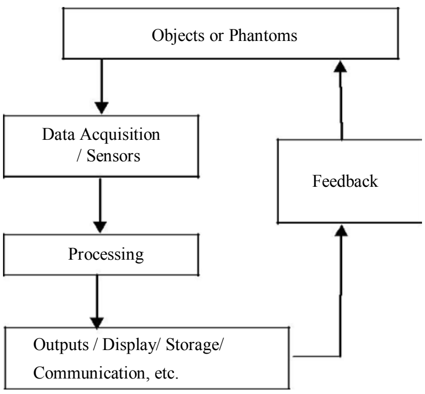

Figure 4: Generalized electrical instrumentation system.

Conclusions

Engineers are involved in the development of electrical instrumentation for nearly every aspect of research, either as a part of a team with professionals or independently. With the rapid development of digital technologies, digital instrumentations are highly demanded to realize data collection, processing, sensing, and storage purposes. In this paper, we investigated the important aspects of data acquisition and electrical instrumentation engineering modelling for learning and recognition purposes. The learning and recognition with data acquisition modelling were discussed. The generalized digital instrumentation modelling was described. Based on those studies, we have applied the understanding to our development of an intelligent impulse noise simulation system using data acquisition and digital instrumentation techniques. Further research will be conducted to validate our system based on experimental measurements and computer simulations.

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