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Computational methods (Artificial Intelligence) in structural analysis of concrete

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Image analysis in materials science is in a certain way quite different from the more common in technical literature image analysis related to understanding visual processes. The difference is related to semantic complications. In the materials science image analysis is mainly of quantitative character. It has its own, specific problems, and there are situations where automatic image processing is difficult or needs frequent intervention of a human operator. A solution may be looked for in application of artificial intelligence methods (AI). Some elementary information on AI is given in the paper, and a simple example is described. Unlike typical procedures of automatic image analysis, which need direct supervision from the operator, various AI computational methods should and can autonomously model relations and reveal rules (sometimes called: *hypotheses*) unknown or even unexpected by the user.

Key words: *image analysis, structure of concrete, artificial intelligence techniques, machine learning, artificial neural networks.*

1. Introduction – qualitative and quantitative image analysis

Important part of IA (Image Analysis) investigations concern problems of computer vision, like high-level image processing, visual processes, and image understanding. Examples of application of the results can be found in IA tasks like assistance in radar detection, in processing of stereo images, in analysis of motion in image sequences, in higher semantic level objects recognition, especially face recognition, in character recognition, document image analysis, etc. All such image analysis proceedings are content-based, and are aimed at qualitative rather than quantitative description. Even if this is not entirely true, as the scopes of both approaches overlap, this type of analysis will be referred to in what follows as *qualitative IA*. In some other wording this concerns a *Computer Vision*, which is understanding images

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using computers, acting at different levels of abstraction. Closely connected are here topics of visual illusions – like ambiguous interpretation, illusory perception and visual inconsistency, which will not be discussed further.

In materials science and in the field of concrete-like composite materials in particular, the present situation seems much simplified from the point of view of the computer vision. The '*scene*' (the 'setting') is well identified, it is usually static, and often the operator knows more or less which quantitative characteristics of the image are to be evaluated. It is so at least in simple cases. But from the semantic point of view, the analysis in materials science may often be much more complicated, due to the lack of knowledge of the operator himself. In the text below the approach to evaluate images for predicting properties of the material will be called: *quantitative IA*.

In the *qualitative IA* the meaning of the image is more or less obvious. The object in the image is usually something well known to the observer – a car, a human, a letter, an inscription, a star in the sky. A human observer can identify them with high probability of a precise evaluation, even if they are seen indistinctly. In the *quantitative IA* the problem may be that of the appropriate discrimination of features to be measured. The paradigm (total of concepts consisting of formal theories, classic experiments, and possibly trusted methods) is that what can be seen in the image of a sample is related to the properties of the material from which the sample has been taken. All that can be measured are 'features', but their definitions involve human perception, which is extremely difficult to model in a machine. From the materials science practice it is known that important is accurate discrimination of certain individual components seen in the sample, like defects of different phases, their precise separation, and then their proper quantification. What actually is '*a defect*' or '*a phase*' may not be obvious at all. Also the factor of the scale, which sometimes may be of a secondary importance in qualitative IA, is of primary importance in the image analysis applied to materials sciences.

Assigning objects or patterns into different classes based on their measurements, behavior, etc., is of principal importance in *Qualitative IA*. In quantitative IA the problem is also the uncertainty about features that should be identified.

In all image analysis problems, both quantitative and qualitative, the processing starts with similar image acquisition. This can be realized using scanning microscope, a video camera mounted on a microscope or on a macrostand, a scanner, or a digital photo-apparatus. Less obvious examples may be images obtained from X-ray Computed Tomography (CT), NMR (Nuclear Magnetic Resonance), Spectrography, etc.

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In quantitative image analysis traditionally applied are special statistical tools, especially mathematical morphology (morphology – study of the size, shape, and structure of distinguishable objects in the structure of materials and of the relationships of the parts comprising them; referring to general aspects of the form and arrangement of the parts of objects), and stereology, (stereology – science of the geometrical relationships between a structure that exists in three dimensions and the images of that structure that are essentially two- or one-dimensional (2D or 1D), which enable deduction of important spatial features of the structure of the composite material under consideration. The concept of shape is quite abstract and it is rather difficult to quantify it. In concrete materials there are no crisp, exact definitions of certain objects under consideration, like pores, cracks and microcracks, entrapped air voids, interface regions, various defects. Their descriptions are usually fuzzy, and the analyst is often uncertain what exactly should be observed.

A good example of the difficulties mentioned above is problem of identification of steel fibres in a cross section of SFRC specimen (*Steel Fibre Reinforced Concrete*). Any laboratory operator can locate the fibres by turning the sample manually, until each fibre reflects some light and is identified. The spot can thereupon be copied manually to a transparent foil, to analyse the distribution of fibres. But in an automatic system a corresponding simple procedure is usually unavailable.

Another example of a similar difficulty is in air void analysis in the air-entrained concrete. It may be easy for the human operator at the microscope to recognize – again after some efforts – whether an object is a void filled with the contrasting substance or it is a white aggregate grain, or to distinguish a real void from a section of a very transparent, glassy grain of the aggregate. It may be impossible or economically unworthy to formulate a sequence of commands for an automatic IA system, to produce an equivalent answer. Here, a human operator is generally more reliable than a machine.

In qualitative IA, and this is especially obvious in medical diagnosis problems, of importance is reliability of the image, and the problem of avoiding false estimates. This is connected among others with problem of artifacts (false representation of non-existing physical objects).

In testing of concrete encountered can be significant difficulties with appropriate and – at the same time – automatic evaluation of the features in the image of the material structure. On the other hand, it is a typical situation when analysing samples of concrete taken from existing construction that known is a certain qualitative attribute of this particular material – its certain 'class' or its certain property. The material may be qualified as *strong* or *weak*, as *frost resistant* or *frost sensitive*, with a *higher*- or *lower*

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resistance to abrasion, etc. In spite of difficulties mentioned before, this "external" knowledge can be exploited by the artificial intelligence methods.

During a typical automatic image analysis human observer is performing actions of perception, understanding and selection of the features to be measured. The IA software and hardware are for the human observer barely very useful tools. All the inference, deduction, and other mental processes concerning the image are left to the operator. The objects of those mental processes are results of the more or less automatic image analysis, associated with the "external" knowledge, which corresponds to the totality of information the operator has obtained.

The typical morphological tools, like low level image transformation procedures, stereology, etc., will always be a primary apparatus to analyze the material structures. In both kinds of IA – quantitative and qualitative – necessary are procedures of low level image analysis – procedures like edge detection, image segmentation, image texture analysis, etc. The possible transformations, filters, various IA operations, etc., are not discussed here, as they are objects of many excellent monographs; cf. for example [33, 39, 44]. All these IA tools produce representations of various physical situations, important for engineers.

Examples of such analysis in concrete technology are images – in different scales, entire or limited to selected ROIs, (Regions of Interest), of fibres, pores and voids, interface regions, systems of cracks and/or microcracks, the meaning of which is obvious enough for any civil engineer. New challenges, however, are brought by rapid development of modern civil engineering technologies and materials. This is the case of multiple new composite materials like HPC (High Performance Concrete), SCC (Self Compacting Concrete), SIFCON (Slurry Infiltrated Fibre Concrete), etc., and new components like silica fume, PFA, superplasticizers, microfibres, and so on. The new components have usually poorly recognized properties, and the engineer who applies the new technologies does not often know yet what is important in the description, and where the attention should concentrate. For example, it may not be obvious whether one should bother about the air voids distribution in VHSC (Very High Strength Concrete). With increasing number of attributes and new properties the whole problem of material quality estimation gets easily multidimensional and therefore still more difficult for human intuition. However, if the user knows from the reports, or from the experience, that certain recorded images of the structure correspond to a '*good*' material, some to '*poor quality*' one, etc., then the human intelligence can be applied to infer regularities from examples. The same action can nowadays be tackled using machines (computers and AI techniques).

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The present paper deals with to the possibility of having some assistance in image analysis from the methods originating from Artificial Intelligence. This promising possibility has been barely exploited yet, but first experiments have already been successful. When image analysis is performed on images related to certain well-defined categories, artificial intelligence methods can either suggest certain general rules (principles) or suggest a numerical answer without any explanation or justification, but being in accordance with previously elaborated examples.

2. The matter to be processed: the databases

All computational tools originating from or related to the artificial intelligence concepts deal with examples. The examples for the machine treatment must be formalized, which means that their form should comply with certain precisely defined conditions. The collection of examples is called *a database*. A database is composed of records. In the simplest case the database can be conceived as a numerical matrix, in which the rows correspond to records, and the columns correspond to different attributes. In general, however, *a record* may be of quite varied nature, and its components do not have to be only numerical. They may be numbers, alphanumeric strings, texts, images, sound tracks, recorded signals, etc.

Information that may be gathered and recorded by human mind is free and open. We can keep in our memory various sounds, images, smells, and even emotions, e.g., a prejudice. Such memory was always necessary for humans to be able to live in the external, often alien world. For the automatic treatment of data, however, the structure of records must be very limited to a number of selected, precisely defined fields.

While in general the content of a database can – as mentioned above – be of varied nature, in this text discussed are only simple so-called attributes of descriptive type. Each field in a record in such a database is referred to as *an attribute*. Basic types of attributes are presented in Table 1.

Most important differentiation of the attributes is the one between quantitative and qualitative descriptors. Many statistical data analysis methods, (e.g. multidimensional regression), artificial neural network algorithms, optimisation algorithms, etc., operate only on quantitative descriptions that are numbers. In the realm of technological problems, the materials, constructions and/or situations may be described also by attributes that are qualitative. Examples of purely qualitative attributes are colours, forenames, manufacturer designations, fuzzy descriptors (like small, medium, large), odours, etc. All those cannot be unequivocally ordered in any impersonal, objective way.

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TABLE 1. Basic types of attributes in a simple, descriptive type database.

Type	Symbolic	Examples
1. continuous	con	$x \in \{x : x > 3.15$ AND $x \leqslant 14.00\}$
2. cyclic	cyc	$x \in \{Spring, Summer, Autumn, Winter\}$
3. identifier	label	any string acceptable by the system
4. linear	lin	$x \in \{1, 7, 8, 11, 72, 356, 1435\}$
5. logical	log	$x \in \{FALSE, TRUE\}$
6. nominal	nom	$x \in \{Basalt, Granite, Limestone, Gravel\text{-}F, Gravel\text{-}C\}$
7. structural	str	$x \in \{r2\text{-}4, r2\text{-}8, r8\text{-}10, r10plus\}$
8. ignored	ign	– can replace any attribute type

In case of such nominal variables a list must be created, that encloses all the possible terms concerning a given attribute.

In addition to the above differentiation the attributes may have different role in a particular database exploited for a given purpose. They may concern to: input or output, reasons or effects, predictor variables or response variables, motives or results – there are different expressions used.

Each experimental database represents a certain knowledge about the physical reality. In the simple case of a purely numerical database, the matrix represents a hidden model, which corresponds to mapping of one-dimensional or multidimensional space of the input values into another, one-dimensional or multidimensional space of the output data. Similar mapping might be conceived also in the case of a mixed database, not purely numerical, containing qualitative attributes, but such dataset can not be processed using traditional linear algebra.

Another complication related to the real-life situations is a possibility that not all the attributes in a database are known indubitably. Certain attribute values may, for example, be only probable, sometimes with a clearly specified probability, and sometimes such value may not be known at all. In the last case, where instead of the quantitative or qualitative value of the attribute a question mark appears ("?") the numerical statistics and many other numerical tools can not be applied. There are many computational methods and tools, however, for example in machine learning or rough sets theory, where the system is expecting to deal with classes rather then with a continuous, numerical description. These methods can process qualitative data, and also to treat the lacking or uncertain data as special, admissible categories.

In the image analysis problems the databases will be mainly composed of results of the automatic image analysis – effects of pre-processing, image

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segmentation, various measurements, etc. All these data may be accompanied by external information concerning the source origin, specimen special treatment, or configuration (settings) of the image analysis stage.

The final step before submitting a database to intelligent processing is its evaluation and cleaning it from outlier records, (that might disturb predictions), removing outlier attributes, and – sometimes also – sorting of the training dataset in a certain optimal way. The procedures are described in specialized textbooks, e.g. [34, 50]. All such measures, however, are beyond the scope of the present paper.

The topic of combining image analysis with artificial intelligence concepts is still relatively new, so the structure of a database for concrete materials analysis must in each case be decided separately. It can be added that what concerns the electronic databases describing in general properties of concrete materials, the problem is still in its introductory stage, cf. e.g. [30].

The additional point to be mentioned here is domain of the database. In the Image Analysis applications it may concern the low level and higher-level processing, that is the texture elements as well as the characteristics of the objects (features) already extracted from images. The database may be a collection of details that characterise several selected images as well as it may cover many images of certain standard form. In both cases it may be accompanied or not by external knowledge, being prepared for supervised or unsupervised learning, which is to be discussed in the chapter below. The way the database is organised should at each time depend on the particular problem and on the expected way of its analysis.

3. Computational methods – techniques of Artificial Intelligence (AI)

Artificial Intelligence (AI) approach is based on 1950 suggestion of Alan Turing that machines could be programmed to mimic the behavior of humans. As "Artificial Intelligence" it was probably named in 1956 by John McCarthy, and this has opened discussion whether a machine, a computer could exhibit intelligent behavior. Later on this led to differentiation between the concept of strong AI and weak AI. The first one is to be capable to carry all human like thinking and reasoning procedures (the actual machine intelligence), and the author of the present text is deeply skeptical about this possibility. Instead, the weak AI concerns only certain ability of a machine to realize automatically particular tasks, especially those corresponding to data regression or classification. This seems quite realistic. The term 'classification' is used here in a very broad sense, and its range is from a simple classification of the groups of numbers up to really complicated classification

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of the human face photographs, or even of the emotions that such pictures may express.

All AI tasks should be done automatically. It is obvious, that when presented a list of well-defined steps to execute each in order, computers outperform humans in speed and accuracy. They operate, however, without having a comprehension of what those instructions are to do. This lack of comprehension is characteristic for all the computer programs used around everyday, no matter how complicated they are. Computer, in contrast to human, but even in contrast to a dog or a mouse, is not a '*being*' in philosophical sense, and can not '*think*'.

The procedures that are often associated with the artificial intelligence, where the list of steps from the beginning to the end is precisely described, belong to the so called Expert Systems (ES), cf. [10], which will not be discussed in this paper. ES solutions may be quite practical in many applications, but in this text the discussion is limited to algorithms where the system (the machine) can automatically modify its action accordingly to the received data. It may be expected that in the future ES solutions will also use elements of the real artificial intelligence, but at present they are usually without possibilities to learn by examples to infer conclusions [10].

It should be added that although a computer cannot '*think*', it is possible to prepare the machine to interact with the expected environment and apparently solving problems. This, however, will not be an '*intelligence*'. On an uninformed human observer similar activity could make an impression of real '*thinking*', (look for example for '*chatterbots*' in the Internet; a chatterbot is a program that attempts to simulate the conversation or "chatter" of a human being – the programs like "Eliza", "Parry" or "A.L.I.C.E."). In creating a similar program its author must define the whole environment – a language with its syntax for the descriptions, preview possible types and domains of attributes, etc., expected questions, etc., but the main intention is to deceive the observer rather than to perform any significant analysis.

AI approach is generally aimed at '*facing the unexpected*'. AI techniques are associated with a number of particular solutions dedicated to diverse tasks, like game playing, e.g. chess, language translation, natural-language understanding, fault diagnosis, robotics, etc. Currently much attention is dedicated to procuring knowledge from information available in electronic form, e.g. on the Internet. Many of those investigations are pure informatics, being far away from the area of materials science. But in the last decades also in Civil Engineering the computational methods, originating form AI, are becoming more and more popular [11, 12, 13, 14, 15, 16, 17, 18, 47, 51, 52]. All these, however, rather seldom concern the problems of image analysis.

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As originating from AI concepts a considerable number of particular solutions have been proposed. These are Artificial Neural Networks techniques, (ANNs), Machine Learning tools, (ML), Genetic Algorithms, (GA), Statistical Structure Recognition methods, Data Mining and Knowledge Discovery in Databases, (KDD). Only few selected from those are discussed in what follows.

There are two basic services that artificial intelligence can render in image analysis. The first one concerns situations where all the data are quantitative. Such is the case of ANNs (Artificial Neural Networks). ANNs are working as *black boxes* that can realize mapping of one multidimensional space into another. It can be added that any algebraic, well-defined function might also be considered as such mapping, provided that parameters of the function were properly defined, (e.g. by regression analysis). In this case, however, there would be no element of learning, and the above act of selection of the parameters of the function cannot replace the phase of the training in ANNs.

The principal difference between the closed algebraic expression and ANNs solutions is that in the former the shape of the transformation (i.e. the mapping) is selected or defined by the user who may eventually be wrong. Only if the user is lucky in picking a successful formula the procedure will bring a good solution. In case of ANNs the user after deciding the architecture of the system (its hardware) is making no further decisions, because the system should adapt itself to the data. A well-formed AI system can not '*be wrong*', (unfortunately, it should not be proclaimed that '*the system is right*' either) – what the system does is simply adapting itself to the data. On the data change the system should change its actions accordingly.

It should then be emphasized that ANNs are trained, and not programmed, as was in case of ES. The effect is similar to the activity of human brain, where spreading activation of neurons results in the ability to think; also to reason, infer, interpret, learn, perceive. On the other hand the ANNs do not contain any innate knowledge. Once the computer is switched-off the network "forgets everything" (of course, if this knowledge was stored to a disk, than it could be re-loaded again). ANNs do very poorly on knowledge-intensive problems – such as diagnosis, planning or natural language understanding, but may be quite effective in knowledge-poor but learnable situations such as motor control, visual number and character recognition or numeric optimization problems.

In ANNs the network is adopting (modifies) its internal *weights*, in the way corresponding in the possibly best way to the dataset under consideration. The dataset does not have to be either a one dimensional relation or to be very regular. The effectiveness of the network will depend, however, on

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the selected architecture, (number of layers of the so called hidden neurons, number of connections, the way the information is processed).

The data to the network is supplied in the numerical form and it is processed digitally. If part of the data is qualitative it is sometimes possible (but only *sometimes*!) to code the attributes into numerical form, but this needs a reliable justification. Such special case is, for example, the situation where the values of the attributes can be ordered, and the effects of applying different values to attributes are expected not too big.

Typical ANN has a complex structure, and contains certain hidden attributes, which are modified during the training. However, the current states of those attributes, called *weights*, is never analyzed nor even revealed to the user (even if it were quite easy to do so). The whole network behaves thereupon like a '*model*', constructed in the convention of a '*black box*', which realizes mapping of independent variables into dependent variables.

The objects processed by ANNs are direct experimental results in form of numbers, digitized sounds, images or other signals. The record resulting from capturing the same image in the IA system, for example a representation of an alphanumeric symbol, can be analyzed in different ways – as an image or as an ordered collection of digits representing such image. The first one can be processed in a cellular network, after using special receptors, which compares two-dimensional collections of pixels that can be activated in different way (these are *images* of pixels). The second one can be processed using a more common feed forward network, analyzing the same image as a series of zeros and ones of a certain characteristic distribution, without no reference whatever to the form of the image.

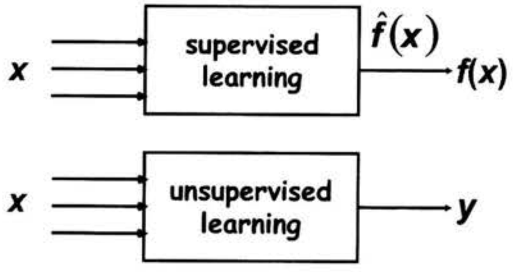

FIGURE 1. Difference between supervised and unsupervised learning. In supervised learning the result of the mapping $f(x)$ of the input data vector x is accompanied by information concerning the wished-for result, e.g., a complete output data vector $\hat{f}(x)$. In the unsupervised learning the only reference for the network are results formed previously by its inference module (only internal criteria can be applied).

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To evaluate the effectiveness of a network the system should be used in training on a selection of the available records, followed by testing the system predictive power on the other records (not used for training). For the more detailed analysis new set of records should be selected for the training dataset, the predictions done on the remaining ones, and the process being repeated many times. When finally the average value of the errors is calculated, this gives the estimate of the effectiveness of the whole system. Such procedure is known as *cross validation.*

There are two basically different modes in which an artificial neural network (ANN) can acquire the knowledge. It may function in terms of unsupervised or supervised learning. Assuming a simplified depiction of ANNs as a mapping of one multidimensional space into another such space the difference between the two modes can be explained similarly to Fig. 1.

Two important examples of ANNs presented below are the networks of the feed forward type and Fuzzy ARTMAP, see Fig. 2 and Fig. 3. Feed forward type ANNs behave finally (that is after successful training, for example with back propagation correction of weights, which usually takes long time) as a continuous function, even if it may be highly non-linear. When presented in the testing phase with a new record, very different from the records in the training set, the network will also generate a certain prediction, even if this is unsubstantiated, for example when the input data corresponds to the locus of discontinuity in the process under consideration.

Discontinuous response is enabled in the ART idea of unsupervised learning (ART – *Adaptive Resonance Theory*), based on quite different neural network concept, where the individual records are classified depending on the

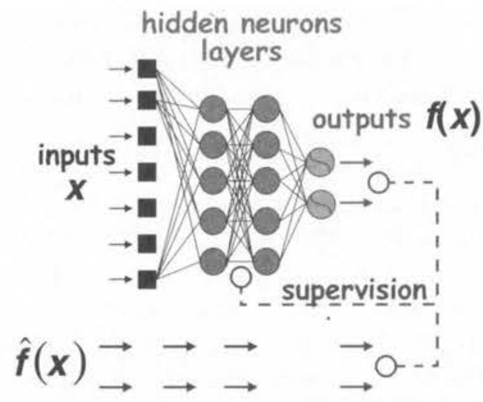

FIGURE 2. The idea of multilayer neural network. Supervision concerns resetting internal weights in the way compliant with the information carried in the input data. Difference between $f(x)$ and $\hat{f}(x)$ is the error of prediction.

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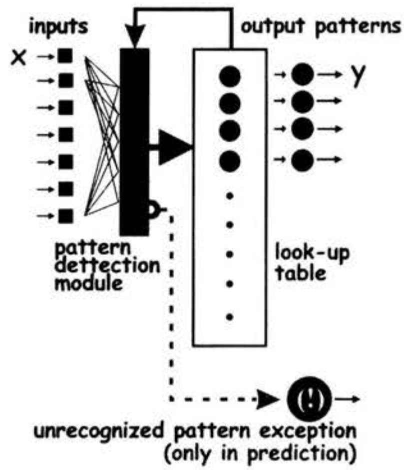

FIGURE 3. The idea of unsupervised solution – concept of ART network solution (Adaptive Resonance Theory). Some patterns among input vectors x remain unrecognised as y, if not encountered previously during training; the case of output marked as: "(!)".

distance between them. Each record is some numerical vector, and the distance between the records is defined applying certain metric, like Euclidean, City block metric, Hamming, etc. The concept of ART has been first proposed by Carpenter and Grossberg [5], and later on developed into supervised network system Fuzzy ARTMAP. In ART solutions during training new 'neurons' are born, creating a kind of a look-up table – Fig. 3, the whole process having a certain likeness to the process of new neural connections forming in the human brain during learning. Fuzzy ARTMAP has been applied successfully to concrete materials in predicting the compressive strength of HPC mixes [12, 18].

In solutions of this kind, when the system is fed with an input record too remote from the previous '*experience*' of the system (which means that the example is too different from the examples presented in the training stage) the program may refrain from giving any answer at all, presenting instead a message equivalent to declaration: "I do not know".

In the Fuzzy ARTMAP solution two fuzzy ART classifiers create stable recognition categories in response to arbitrary sequences of input patterns: in the domains of predictor variables and response variables, respectively. Each of these operates in an unsupervised mode. However, the two systems in a group act in the supervised mode: each predictor information is accompanied by a response variable (in the training stage, not so during testing!).

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An example of another approach is Hopfield network, which is at the same time an example of an associative memory. A pattern consists of an n-bit sequence of 1 s and -1 s, (or 1 s and 0 s), so it may represent a binary image. In the Hopfield net every node is connected to every other node in the network, see Fig. 4. Each connection has an associated weight. Signals can flow in either direction on these connections, and the same weight is used in both directions. Assigning weights to a Hopfield net is interpreted as storing a set of example patterns. After the storage step, whenever a pattern is presented to the net, the net is suppose to output the stored pattern that is most similar to the input pattern. All this resembles biological brain ability to recognize image patterns.

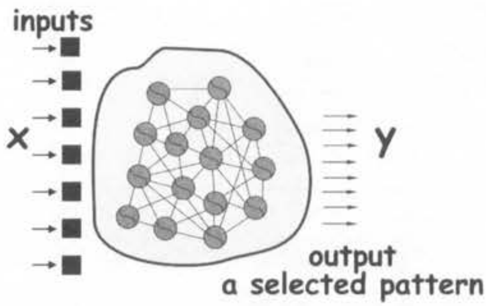

FIGURE 4. Hopfield network (unsupervised) may classify patterns according to their similarity to the patterns frequently observed during training, which embossed a certain combination of internal weights specific for the data.

There are plenty of different ANNs architectures, concepts of training, identification of records, and prediction of the results. Those methods are not discussed here more deeply and the reader is referred to as there is a rich bibliography of ANNs [2, 28, 31, 46], etc. Also the mathematical details of the solutions are not discussed here.

Special ANNs solutions can be applied in some qualitative IA problems. For example, cellular ANNs can be applied for qualitative IA when some '*general meaning*' is expected to be found in the image, like in the Hopfield network.

The second important function that can be realized by special AI methods and tools is generation of rules. This is domain of Machine Learning (ML). The procedure is always realized on a specified set of the results (a sub-set of the database), which is identified by a descriptor, an attribute, an affiliation of the group of records to certain class or category. For example, in a given database, a subset of examples declared as '*good*', or '*medium*', or '*bad*'. The ML program fed with one or more of such subsets (usually needed are

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also accompanying so called '*background examples*'), is formulating a rule, in terms of conditions on the attributes of the database. The rules have the form of implications, conjunctions, and disjunctions, sometimes even negations. They are almost directly interpretable or easy to translate into everyday language [8, 19, 24, 25, 26, 28, 36].

The idea of the ML procedure is illustrated in Fig. 5. Examples of ML techniques in concrete materials studies can be found in [17, 48, 49].

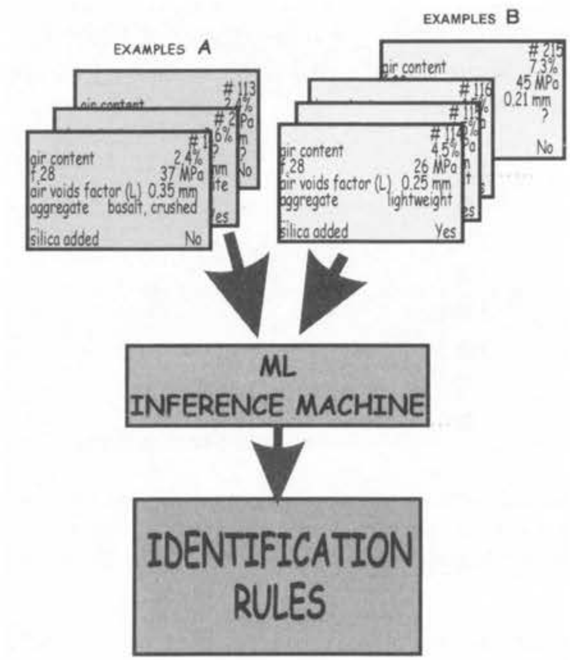

FIGURE 5. Machine Learning (ML) procedure. The system (its inference machine) is trying to formulate rules (hypotheses) that enable recognition of membership of a record to one of the groups presented during training (Examples A, Examples B, etc.). The records contained information on the properties of tested concrete specimens.

Usually the ML program has many parameters that allow for more narrow or more broad scope of searching during creation of the rules. Their choice allows or prevents exceptions from certain proposed rule.

In classical correlation or regression analysis the aim is association between variables. There is a hidden assumption that the whole description can be perceived as 'frozen', that is unchanging. Instead the ANNs systems were conceived assuming situations similar to those faced by the living beings: the system is to react to the environment that may be constantly changing, supplying new facts and situations. The same concerns typical ML solutions

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and all AI systems should basically be able to learn continually and, if necessary, to change even their "paradigms", whatever the term "paradigm" could mean for a non-living system.... A number of different machine learning programs was reviewed in [20].

An additional help in constructing computational tools can be obtained from Genetic Algorithms approach (GA). GA combined with other AI tools enable so called hybrid solutions. The idea of GA is examining in parallel a number of solutions of the problem and making selections. The system is more or less randomly changing records describing solutions, looking for the '*mutations*' that are closer to the optimum.

The solutions are described with typical wording like '*population*', '*parents*', '*offspring*', etc. One possible idea is to use GA to search for a better organization of given ANN:

- start with arbitrary setting of the network parameters,
- make random changes,
- check the new effectiveness of the network,
- if what was done improves the effectiveness use the last solution to generate next generation of solutions, which are expected to be better,
- discard the older solutions and try again.

Selection of the better combinations of the attributes is identified with multiplication and survival of '*chromosomes*'. By repeating the action many times a kind of Darwinian type evolution proceeds and eventually produces solutions close to optimal; the result is elimination of the less adapted "chromosomes".

4. Artificial intelligence and image analysis problems

There is a basic question whether and which functions of the AIA (Automatic Image Analysis[1)]), as summarized e.g. in the special issue of *Cement Concrete Composites* [7] can be entrusted to actual, real control by the artificial intelligence. As discussed by Chermant [7], by measuring size, dispersion, distribution, orientation, shape, number etc., of objects in the image, or amount of observed components, and by evaluating changes of such quantities under actions like temperature variations, mechanical loading or environmental phenomena, it is possible to obtain valuable characterisation of the material and to estimate its quality, for example its physical properties [7]. The above statement represents the fact, that the so called '*automatic*' IA

[1)] In this text three slightly similar acronyms are used as follows: AI – Artificial Intelligence, IA – Image Aalysis, AIA – Automatic Image Analysis.

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analysis (AIA) is actually only 'semi-automatic', because there is always a human operator who is to decide operations, to apply filters, to choose what is to be measured. It is the opinion of the present author that at least some of such decisions can be really controlled by AI measures.

Of course it should be remembered that there are yet various natural limitations on the AI methods, for example in what concerns higher levels of morphological analysis. It seems for example barely possible at the moment to effectively apply AI in tasks of estimation of 3D morphological parameters, like number of particles per unit volume. This magnitude cannot be obtained by purely stereological methods without introducing hypotheses or using serial sections. The problem can be dealt with, in a special way, by simulation of the microstructure, applying probabilistic model (Boolean scheme) or Voronoi partitions (random sets, dead leaves model) [6], but this needs human intelligence, not AI.

Speaking in general terms there are two different ways of mathematical characterization of images. In *deterministic image representation* the image functions are related to the point properties of an image, and the neighborhood of this point. In *statistical image representation* the knowledge about the image is related to the average properties [33]. Both types of approach generate data that can successfully be used in general evaluation of the material.

By application of procedures of automatic image analysis (AIA) it is possible to extract varied objects from a typical image of a sample of concrete, and to get almost unlimited number of different numerical information. Various ensembles of numerical data (records) can be obtained by processing colour, grey levels or black and white images, constructing histograms of numerical characteristics of collections of selected objects, of forms enhanced by operations of opening, erosion, etc. The attributes corresponding to such components can be Boolean variables, natural or rational numbers, also vectors, e.g. air-voids distribution histograms. The AI system is to operate on collections of records creating a database. From AIA only numerical databases can be obtained directly, but certain computational procedures can analyse also quantitative parameters, like classes or categories.

Only selected components of such records seem meaningful in the estimation of materials, and a few have been reported to be measured in analysis of concrete. Examples concerning the latter are:

- concrete pores characteristics, air-voids distances, morphology of voids,
- morphological characteristics of ITZ (Interface Transition Zone),
- regions of particular processes of hydration, their distribution, etc.,

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- dispersion, mean distance and orientation of selected phases, especially their homogeneity,
- grain size of particles of aggregate or non-hydrated cement powder, aggregates grain size distribution,
- 2D and 3D analysis of fracture surfaces,
- morphology of microcracks and their orientation.

In modern image analysers special routines are available to automatic measurement of many numerical descriptors of features, like – for example – area and perimeter of distinct and rounded objects, or length, thickness and curvature of elongated objects.

As it was mentioned above in case of ANNs, there are two basically different modes of AI tools functioning. The system is trained either as *supervised* or *unsupervised*. In the first case the input information to be processed is accompanied by some explanatory information, like output data of a process, observed reactions of the material, classification of each record. For example an image of a concrete-like composite may be accompanied by the information on the actual quantity of some particular component used in the mix. In the supervised mode the system can learn from the examples what is the actual correspondence between the input data and the output information. Sometimes the supervision results automatically from performing simultaneously separate measurements in parallel.

In the second case, i.e. in the unsupervised mode, only the input information is applied to the system, and the system by itself is to elaborate the concept of *similar* records. From certain point of view, the records are '*similar*' depending on the accepted metric, in case of purely numerical data, or on special topological concepts in case of mixed data. The programmer of the system naturally suggests the choice of metric and other similar details.

In both cases the system can finally either to model the real behavior of the phenomenon under consideration or to formulate hypotheses (rules) concerning combination of features (attributes) typical for selected subsets of the input database.

The records resulting from the quantitative image analysis can be characterised either internally, by certain combination of attributes, or externally – by certain information accompanying the given image. Both characteristics have to be supplied (indicated) by the user of the system, so most of AI processes in the image analysis will really be of the supervised type. Unsupervised automatic data analysis is more natural in the case of qualitative IA; for example, in recognition of letters by ART neural network [40, 46].

An introductory step to the AI image processing is to decide:

- What image characteristics are to be extracted?

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- How this information is to be extracted?
- How should it be represented?
- How should this information be used to perform the task?

Conscious decomposition of the human perception into formal, procedural steps may be difficult, and it usually needs certain effort and imagination to realize at all where the real problem is. The task is complicated by poor visibility, ambiguity of images, their inconsistency and even visual illusions. Practical effect of the situation is that applications of AI in quantitative image analysis are rare.

The concept of application of ANNs in IA has been tried by Adeli [1], who integrated genetic algorithm with error backpropagation multilayer neural network. The weights of the neural network were encoded as decision variables in chromosomes. The reported examples dealt with image recognition in case of numerals and faces recognition problems. The examples seem typical enough, as in the Internet a list of neural networks related to IA from the last two decades, is above 350 references long, but all of those seem to be dedicated to the Qualitative IA[2].

From the same review by Adeli [1] it can be seen that rare applications of AI to IA concern very particular studies, with the results being obtained at a great computational effort. In a relatively simple problem of recognition of seven by seven binary images, using an ANN of three layers (of 49, 99 and 10 nodes, respectively), and the content of the images being 10 numerals: $\{0, 1, 2, \ldots, 8, 9\}$, there were 5950 weights to set in the system, and the problem was by the author classified as a "large-scale" and "hard-to-learn" [1]. In this paper there was even a suggestion that similar complications need high-performance parallel machines and supercomputers, and hours or even days of computing on normal computers; the paper, however was published in 1993. The above observations show that the efficiency of the approach may be very limited if using inappropriate methods are applied.

A similar picture, concerning the abundance of the qualitative IA and scarcity of quantitative IA, especially the one applied to materials science, can be seen in the large overview published recently [9]. In the special edition of the specialist concrete materials review there was no reference to AI applications either [7]. Most of the problems discussed and related to the image analysis and AI belong rather to qualitative IA, notwithstanding the circumstance that the complications encountered are often related to the basic image processing, e.g. cleaning of noisy images.

Convincing example of quantitative IA application of artificial intelligence tools is somewhat complex case of image analysis in medicine [37], which

[2] Confer: `http://www.cs.uu.nl/people/michael/nn-review.html`

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concerns screening mammograms (X-ray pictures). The ambitious aim of its authors was to get a 95 percent accuracy rate of automatically discriminating normal mammograms from those that indicate possible cancers, which as the authors claim is equally good or better than the best human experts (the mammographers) can do today. Clinical medicine and radiology involve complex decision making without the aid of defined algorithms. Neural networks are designed to handle inexplicit complex systems. The case is recalled here since due to a certain resemblance to material structure investigations a similar solution could be studied also in case of concrete materials images.

Reinus (Washington University) and his colleagues proposed to use neural networks as interpreting classifiers for imaging studies and as predictors, the ultimate goal being direct image interpretation of images using such (neural network-based) classifiers. Their focus was on diagnosing mammograms. Preliminary work with digitized mammograms was found effective in identification of mass lesions directly from the images without human intervention [37].

The method combines wavelet transforms and artificial neural networks to create a system capable of mathematically "reading" images. Wavelets are algorithms that interpret features of an image or other data. An artificial neural network analyzes the above information to decide whether the information matches a correct mathematical pattern. The mammogram images are digitized and turned into format appropriate for the processing by the artificial neural network. The wavelets transform the pixels into representations of very fine features of the image separating them into a mathematical hierarchy, and so the wavelets separate the features of the images into two subsets, one the standard, or control, the other concerning anomalous records, where the disease symptoms are present.

A special artificial neural network software (LOSRAAM, developed by Kalman and Kwasny) detects six distinct, recurrent "internal states", or distinctive features, out of the one to four million pixels in each image. These features are made obvious by a signature clustering of mathematical values, representing each feature. The networks, working in harmony, come into the process at different starting points, each one responding to the digital data and voting "yes" or "no" on what it reads. One overriding network gathers all the votes from the other networks and states a final answer.

The approach involving wavelet transform techniques seems to be a really effective solution, as can be seen from the more recent publication [35], where a four-channel wavelet transform was used for image decomposition and reconstruction, with a novel Kalman-filtering neural network being used for adaptive subimage selection.

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In another example, also from the medicine area, certain soft computing methods were applied in the analysis of computer tomography records [3], where artificial neural networks have been applied to process database containing multiple information from images. The procedure was based on finding anomalies in geometric figures and attributes of the database were like: *Shape* {circular, ovoid (image in plane of greatest diameter)}, *Edge definition* {poor, moderate, well}, etc., that obviously were introduced into the database manually by the operator, or by an expert evaluating the radiograms. This was a case of supervised learning.

It can generally be assumed that the user has some prior knowledge and can rationally select the parameters that AIA system should measure and store in the database. What concerns the technical details all the problems discussed here may look different in case of different image sources and in different magnification scale; for example, a microscope and CCD camera, a scanning electron microscope and backscattered electron imaging, a digital photo-camera, a flat-bed scanner, etc. As images are sometimes degraded, artifacts may appear in them, virtual features, and it is the operator of the system who should exclude them from further processing. In certain way the brain of human will act here as a complex stereological / morphological device, which can be automated only with great difficulties.

In qualitative IA the differences that are searched for may be related to analysis of separate unique images, groups of images or to a permanent analysis of the same, changing image. For physical reasons some of these cannot be realized in particular situations of quantitative analysis. Various interesting solutions were applied in an apparently quite remote field of ATR, (Automatic Target Recognition), in laser radar imagery [43] where, for example, classifications of an object in the image were correctly based on:

1. eccentricity of object shape,
2. standard moment m_{01} (horizontal coordinate of the shape centroid),
3. maximum gray level,
4. kurtosis (4th order statistic) of gray levels,
5. a measure of fractal dimension of gray levels.

The data supplied by an automatic image analysis system (AIA) enclose varied information. Important features can be enhanced by application of appropriate edge detection algorithms [53]. More sophisticated procedures can indicate differences in texture. Important information can also be obtained by fractal analysis [22].

Artificial Neural Networks (ANNs) are therefore a recognized tool in image analysis [27]. Inductive techniques seem to be much less used in image

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analysis than solutions involving ANNs. A basic study of this possibility was presented recently in the dissertation [21].

Various information collected by means of automatic IA (AIA) can be processed in any arbitrary way decided by the operator but, quite obviously, various settings of the system can be optimized. The general idea of possible treatment of the image data with modern computational tools is shown in Fig. 6. In this image units marked with terms "INFERENCE" and "SELECTOR" represent possible program modules based on the concepts of artificial neural networks, machine learning, genetic algorithms, etc.

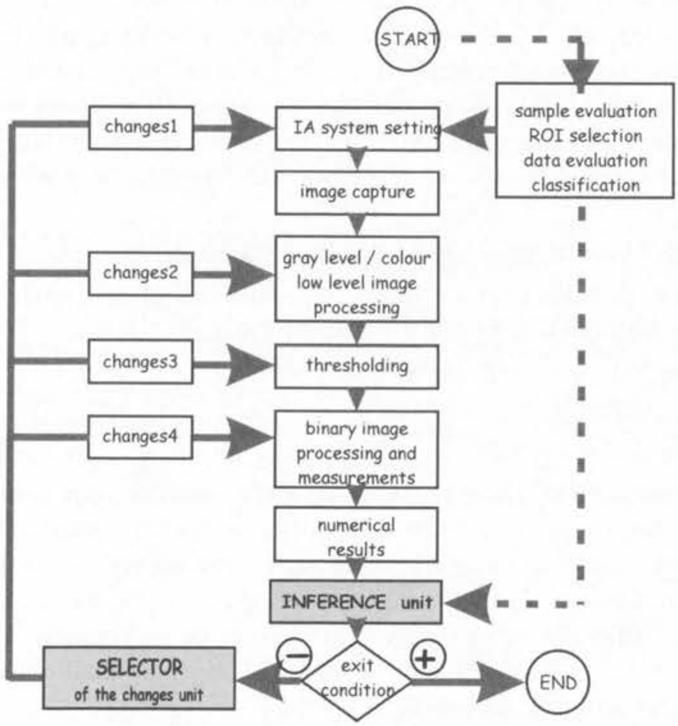

FIGURE 6. General idea of possible image analysis treatment using AI methods. In this example AI techniques are limited to two blocks only (marked as INFERENCE and SELECTOR). All the other elements correspond to conventional automatic image analysis. The dashed line represents transfer of "external" information corresponding to a given sample (or a given ROI – Region of Interest in the sample).

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5. AI application in structural IA problems

5.1. Identification of the air voids in concrete

We pass to a detailed discussion of the idea of practical processing of the image analysis data using artificial intelligence methods.

The problem concerning the analysis of air voids distribution in hardened concrete was as follows.

To estimate the air voids structure in concrete according to Polish new standard PN-EN 480-11/2000, one needs an identification and evaluation of the system of the *regular* pores, usually seen as the separate circles – e.g. white on blue or black – of diameters mainly between $10\,\mu$m and $50\,\mu$m. The preparation of the surface of a concrete sample, its grinding, polishing, staining and introducing contrast to enhance the air voids should improve the quality of the image, but the preparation is never perfect. There should be no need to separate overlapping particles present in the image, but practically the operator encounters a whole spectrum of different features white on black. There are:

- agglomerates 2, 3, or more voids in close contact,
- regular entrained air objects – separated small and medium size air voids with maximum size of $0.010\div1.0$ mm,
- entrapped air – irregular air voids of all sizes,
- filled voids,
- cracks and voids along aggregate/paste interface discontinuities.

The presence of all these must naturally be recorded, but not all of them should be taken into account in calculation of the air entrainment characteristics. Some of them may be artifacts or may be related to presence of microcracks. Some of them should be counted as 2 or 3 objects, not a single air void. Classification of the objects to be counted and measured must then be done manually, (identifying and flagging of the individual objects), which increases time and cost of testing.

The idea of application of AI approach is that during the automatic image analysis (AIA) the system should identify by itself and separate the non Air Entrainment air voids, without respective information being supplied by the operator. This can be done by finding the identification rules from examples [52]. Such rules will enable sorting and rational selection of the records. Two machine learning (ML) programs have been used for this purpose – aq19 and See5, cf. [25, 36].

For the experiment a database of 2504 '*white objects*' evaluated by Image ProPlus software have been collected from three concrete specimens, pre-

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pared for the standard air voids analysis. The database was collected from two photographs (*1_pc* and *2_pc*; taken at magnification of the stereoscopic microscope 30×), of correctly air entrained concrete, and one photograph of poorly air entrained concrete (*2_ik*).

For the training all 2504 objects extracted by the AIA have been evaluated by an expert (the operator) in such way that to each single object a label has been assigned, indicating whether the object was an air entrainment air void (1776 cases) or some entrapped air or another non-air entrainment air void (186 cases). In case of 542 objects the expert restrained from deciding what is the nature of the object, marking such objects with sign "?" (class: *uncertain*).

The labels for the three classes: {Air Entrainment Void, Non Air Entrainment Void, Unclear Case}, were respectively: {T, N, Q}. The Unclear Case, {Q}, concerned objects where the operator could hardly decide as for the nature of the object.

Each object have been characterized by 8 attributes generated automatically after the threshold operation on Image ProPlus IA system. The 8 attributes for each object were:

- *Area* (A) of the object, [mm^2],
- *Aspect* (As) – ratio of the major to minor axis of the ellipse of the same area and the same moment of inertia as the object, units: [-],
- *Area/Box* (AB) – ratio of the area of the object to that of a of a rectangle circumscribed on it, [-],
- *Box X/Y* (XY) – ratio of width to height of such rectangle, [-],
- *Radius Ratio* (RR) – ratio of maximum distance from centre of gravity of the object to its border, to minimum such distance, [-],
- *Roundness* (Ro) – coefficient defined as:

$$\frac{(\textit{perimeter of the object})^2}{4\pi A}, \ [\text{-}],$$

- *Size* (W) – width of the object, [mm],
- *Fractal Dim* (FD) – fractal dimension of the object according to Image Pro Plus (only in case of objects larger than 30 pixels), [-].

One *derived* attribute, *Der*, has also been introduced into the database, mainly for demonstration purposes. It was calculated as a product of the three primary attributes: *Ro*, As and *RR*, normalized so as to keep the the value of *Der* in the range $(0, 1000)$.

The above characteristics have been selected from among 31 different numerical features offered as built-in functions of the Image ProPlus. There

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were also additional information recorded in the same database, that have been disregarded later on:

- image identification number {1_pc, 2_pc, 2_ik},
- background characteristics {Z, U, K, R, Od, Ob, W},
- number of pores clustered $\{1, 2, 3, 4, 5, 9\}$.

Exactly from the last of the above attributes the classification of the objects has been introduced, resulting in labeling them with numbers of interconnected circles, even if they were recognized by the Image ProPlus as a single binary object.

TABLE 2. Factors used in normalisation of the data from Image Pro Plus.

Parameter	Symbol	Range	Factor
Area	A	0.000015÷2.159781	10^6
Aspect	As	1.000÷9.303	100
Area/Box	AB	0.253÷1.000	1000
Box X/Y	XY	0.238÷9.583	1000
Radius Ratio	RR	0.005÷124.589	1000
Roundness	Ro	1.000÷5.037	1000
Size(width)	W	0.000÷1.231	1000
Fractal Dim	FD	0.000÷1.320	1000

To unify the notation the attributes in the database have been multiplied by certain factors (constant numbers) and were approximated by rejection of the decimal fractions, see Table 2. After rejection of 6 uncertain records the final structure of 2499 records database, matrix 2499×10, is explained in Table 3.

An example of the database layout is shown in Table 4.

During the experiment special emphasis was put on rules describing the objects not being entrained air voids. Excerpts from the input scripts for the both ML programs – AQ19 and See5, respectively, are shown in Figs. 7-10.

Results, rules presented in form of conjunctions, obtained in the experiment involving machine learning programs AQ19 and See5, as described in [51], are recalled in Table 5 and Table 6.

The accuracy of rule was defined as the number of the records positively not being pores to the total number of recognized records. Accuracy of the rules in Tables 5 and 6 was defined as $\frac{N}{C} \cdot 100\%$. Here:

C – total number of records satisfy the rule from whole database,

N – number of correctly detected objects, not being entrained air voids.

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TABLE 3. The structure of the database matrix prepared for ML analysis.

Feature attribute	Symbol	Meaning	Units	Domain	Function
1. *Area*	*A*	area of measured object	[mm^2]	15÷2159781	input
2. *Aspect*	*As*	ratio between major and minor axis of ellipse equivalent to object	[-]	100÷930	input
3. *Area/Box*	*AB*	ratio between area of object and area of its bounding box	[-]	254÷1000	input
4. *Box X/Y*	*XY*	ratio between width and height of the object bounding box	[-]	238÷9583	input
5. *Radius Ratio*	*RR*	ratio between maximum and minimum distance between object centroid and outline	[-]	5÷124589	input
6. *Roundness*	*Ro*	shape factor defined as $\frac{perimeter^2}{(4\pi Area)}$	[-]	1000÷5037	input
7. *Size*	*W*	(width) – Feret diameter along the minor axis of object	[mm]	0÷1231	input
8. *Fractal Dim*	*FD*	fractal dimension of the outline of the object	[-]	0÷1320	input
9. *Derived*	*Der*	a function of other attributes	[-]	0÷1000	input
10. *Category*	*T_N*	specification of the air void object (number of spheres from air entrainment – T, or entrapped air – N, or: 'uncertain' – Q)	[-]	{ Nob1, Qob1, Tob1, Tob2, Tob3, Tob4, Tob5, Tob9 }	output

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TABLE 4: Example of records from the database specified in Table 3.

No.	A	As	AB	XY	RR	Ro	W	FD	Der	**Type**
1	1356	109	742	938	1385	1057	40	1063	2	Tob1
2	1311	200	652	1833	5662	2685	30	1233	31	Tob1
3	6751	102	668	1147	1305	1342	96	1088	2	Tob1
4	1112	108	802	929	1247	1000	34	1063	1	Tob1
5	137	182	750	667	4714	1004	9	0	9	Qob1
6	30	100	1000	1000	5	1000	3	0	0	Qob1
...	...	...	...	...	...	...	...	...	...	...
2448	3353	116	765	1087	1324	1099	61	1068	2	Tob1
2449	411	206	701	1571	12167	1317	15	0	34	Tob1
2450	46	163	1000	667	8	1000	3	0	0	Nob1
2451	30	100	1000	1000	5	1000	3	0	0	Qob1
2452	457	264	536	571	5192	1546	16	1083	22	Tob1

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TABLE 5. Examples of rules generated by AQ19.

No.	Obtained rule	Number of records supporting the rule				Accuracy of the rule [%]
		total	not AE void	AE air void	(?) unknown	
1	$[A=83.81\ldots921.99]$ $[As>126.64]$ $[RR>2391.77]$ $[W>3.42]$ $[FD<1228.28]$	243	40	142	61	16.5
2	$[A=1847.80\ldots9905.78]$ $[As>150.24]$ $[RR>2795.76]$ $[W>32.70]$ $[FD<1110.11]$	23	9	13	1	39.1

TABLE 6. Examples of rules generated by See5.

No.	Obtained rule	Number of records supporting the rule				Accuracy of the rule [%]
		total	not AE void	AE air void	(?) unknown	
1	$Nr\_Z = 2\_pc$; $A>76.19$; $As>201.87$; $Ro\leqslant 1037.78$; $W\leqslant 5.86$	8	4	1	3	50.0
2	$Nr\_Z = 2\_pc$; $A\leqslant 9433.35$; $XY\leqslant 1291.67$; $RR>2823.96$; $RR\leqslant 3206.43$; $Ro>1256.5$; $Ro\leqslant 2614.84$	7	6	1	0	85.7

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```
parameters
run  ambig  trim  wts  test criteria
 1    pos   mini  cpx  e    default

default-criteria
# criterion tolerance
1 minsel 0.00

variables
#    type   levels  cost   name
1    con    1    1    A.A
2    con    1    1    As.As
3    con    1    1    AB.AB
4    con    1    1    XY.XY
5    con    1    1    RR.RR
6    con    1    1    Ro.Ro
7    con    1    1    W.W
8    con    1    1    FD.FD
9    con    1    1    Der.Der

Nob1-events
# A As AB XY RR Ro W FD Der
149 5174 179 518 1281 3619 2695 78 1110 18
2382 30 100 1000 1000 5 1000 3 0 0
192 30 100 1000 1000 5 1000 3 0 0
......
Tob2-events
 # A As AB XY RR Ro W FD Der
 914 36072 164 653 1522 2353 1592 197 1076
....
Nob1-tevents
# A As AB XY RR Ro W FD Der
149 5174 179 518 1281 3619 2695 78 1110 18
2382 30 100 1000 1000 5 1000 3 0 0
....
```

FIGURE 7. Excerpts from the AQ19 input script.

In these preliminary experiments the rules generated by programs AQ19 and See5 were insufficient for fully automatic elimination of all erroneous objects, that is objects considered to be NOT air entrainment air voids, without removing simultaneously many regular, properly shaped air voids. It was found, however, that assuming a rule resulting from these experiments, that rejected should be objects characterized by the set of attributes: *Radius Ratio* > 3.7, *Roundness* > 3.5, *Width* < 0.2 mm, a number of parasitic objects could be eliminated. After objects with shape factors performing

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```
  Qob1-outhypo
    #   rule
    1   [A<91.00] [AB>750.00]
                          (t:420, u:420, f:0, n:383, q:20.0912)
    2   [A=99.00..152.00] [As>133.50] [W<9.00]
                          (t:38, u:38, f:0, n:45, q:4.38701)
....
  Tob1-outhypo
    #   rule
    1   [AB>640.00] [RR<2276.00]
                         (t:1359, u:1359, f:0, n:588, q:36.0892)
....
```

FIGURE 8. Excerpts from the AQ19 output script.

```
Type. | the target attribute

No:label.
A:continuous.
As:continuous.
AB:continuous.
XY:continuous.
RR:continuous.
Ro:continuous.
W:continuous.
FD:continuous.
Der:continuous.
Type:Nob1,Qob1,Tob1,Tob2,Tob3,Tob4,Tob5,Tob9.

attributes excluded: Ro,Der.
```

```
1,1356,109,742,938,1385,1057,40,1063,2,Tob1
2,1311,200,652,1833,5662,2685,30,1233,31,Tob1
3,6751,102,668,1147,1305,1342,96,1088,2,Tob1
4,1112,108,802,929,1247,1000,34,1063,1,Tob1
5,137,182,750,667,4714,1004,9,0,9,Qob1
6,30,100,1000,1000,5,1000,3,0,0,Qob1
....
2502,2126,582,727,6000,10149,2922,20,1076,178,Tob1
2503,556,172,570,2000,3869,1635,22,1089,11,Tob1
2504,15,226,1000,2000,6,1000,0,0,0,Tob1
```

FIGURE 9. Definitions file (above), and excerpts from See5 data script (below).

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```
See5 [Release 1.15]     Wed Oct 09 21:27:00 2002
-------------------
Class specified by attribute 'Type'
Read 2499 cases (11 attributes) from demo.data
Decision tree:
W <= 13:
:...W <= 6:
:   :...XY <= 1100: Qob1 (710/315)
:   :   XY > 1100:
:   :   :...XY <= 1412: Tob1 (23/8)
:   :       XY > 1412:
:   :       :...Ro > 1030: Qob1 (3)
:   :           Ro <= 1030:
:   :           :...AB <= 833: Qob1 (3/1)
:   :               AB > 833: Tob1 (64/35)
:   W > 6:
:   :...As > 222:
:       :...XY > 1769:
:       :   :...RR <= 7718: Nob1 (3)
:       :   :   RR > 7718: Tob1 (4)
:       :   XY <= 1769:
:       :   :...RR <= 3449: Nob1 (4/2)
....
Evaluation on training data (2499 cases):
        Decision Tree
      ----------------
      Size      Errors
        72  494(19.8%)   <<
       (a)   (b)   (c)   (d)   (e)   (f)   (g)   (h)    <-classified as
      ----  ----  ----  ----  ----  ----  ----  ----
        32   100    53     1                            (a): class Nob1
         2   445    91                                  (b): class Qob1
         7   223  1453     4                            (c): class Tob1
         1           5    55     3                      (d): class Tob2
                     1          19                      (e): class Tob3
         1                             1                (f): class Tob4
                                       1                (g): class Tob5
                     1                                  (h): class Tob9
Time: 0.2 secs


aaaa
```

FIGURE 10. Excerpts from See5 results script.

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the describing rule were removed from the collection (this corresponded to introducing corrections into the image), it was verified by filtering the whole database in MS Excel, that improvement in estimation of the spacing factor $\bar{L}$, and other air voids system characteristics was on average about 3%, while the manual removing of wrong objects from image was giving improvement about 10%, (with respect to the results of the measurements without any object filtration).

It was observed that in case of good quality of measured concrete sample influence of wrong objects on test results is small, but if the quality of material is poor the influence of the erroneous object increases, which justifies the procedure. Such filtration of features is designated mainly to removal of cracks, which occurred in practical situation and produced errors during automatic measurement of the air void parameters.

5.2. Other possibilities

The examples discussed below are not related to materials science investigations. Still less they are related to image analysis in concrete. The papers on application of image analysis in concrete materials, like e.g. [38], or the other papers in the same special issue of CCR, do not concern artificial intelligence approach. The methods of AI described outside of the concrete technology area seem, however, to be general, so they could be applied also to structural analysis of materials.

One such example concerning IA is detecting and characterization of interior defects in hardwood logs by automatically labelling features in computer tomography (CT) images, where ANN classifier was trained to label each non-background pixel of the image. The obtained accuracy was above 91÷95% [41, 42].

Another example concerns identification of a person by recognition of his or her iris pattern, that is a strongly individual feature. Although the problem is basically that of qualitative IA the pattern of iris is not known in advance, so the system must create by itself standards to compare. The whole procedure of processing the iris image, its normalization, extraction of features by wavelet transform, as it was done in [23], can be presented as a model procedure. The feature vectors were there used for training of LVQ neural network, (Learning Vector Quantization), to recognize cases encountered previously during training. It seems possible that similar procedure could be applied for identification of textures, e.g., in identification of aggregates in a cross section of a hardened concrete sample.

Still another example concerns selection of attributes to analysis, described by Parkinson [32]. The results of an experiment show that magni-

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fication, image orientation and threshold settings may have little effect on the estimate of fractal dimension. Trabecular bone submitted to image analysis has a lower limit below which it is not fractal ($\lambda < 25\,\mu$m) and the upper limit is $4250\,\mu$m. There are three distinct fractal dimensions for trabecular bone (sectional fractals), with magnitudes greater than 1.0 and less than 2.0. It has been shown that trabecular bone is effectively fractal over a defined range of scale. Also, within this range, there is more than 1 fractal dimension, describing spatial structural entities. Fractal analysis is a model independent method for describing a complex multifaceted structure, which can be adapted for the study of other biological systems. This may be at the cell, tissue or organ level and the approach complements conventional histomorphometric and stereological techniques. The same approach seems very appropriate for materials science investigations.

The paper by Adeli [1], on AI methods has been published as concerning image analysis for civil engineering applications, but it seems to be a typical example of limiting the artificial intelligence approach to recognition of the known elements of the reality. It was a qualitative IA approach, and so are most of the available examples, where a complex algorithm using ANNs and

TABLE 7. Examples of AI software for data analysis.

Program	Algorithms	Remarks
1. **MatLab Neural-Networks**	various types of ANNs: BP, RBF, SOM, etc.	only complete, quantitative attributes
2. **Beton**	Fuzzy ARTMAP network	only complete, quantitative attributes
3. **aiNet**	pseudo ANN, predictions by selection of optimal estimator	only complete, quantitative attributes
4. **AQ19**	ML inductive inference program	large possibilities of fine tuning
5. **See5**	ML-decision tree classification program	user friendly
6. **MatLab Statistics**	nonlinear regression, PCA, cluster analysis, etc.	mainly complete, quantitative attributes
7. **GradeStat**	Grade Correspondence Analysis, outliers identification	data preparation and evaluation
8. **SPSS**	most statistical algorithms, K-means cluster analysis, Factor Analysis, etc.	rather costly
9. **Rosetta**	Rough Sets analysis	freeware; too many specific rules generated

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GA tools were applied to recognize digits, and nothing else than ten digits, $\{0, 1, 2, \ldots, 9\}$, were expected in the images database. It should be observed that the applied feed forward and momentum backpropagation algorithms seemingly had very low convergence rate, at least if compared with the experiments of the present author using ART family ANNs architectures.

The concept of direct application of ANNs in more basic processing of images is rather modestly described. The idea of image compression, self organizing maps for image segmentation, and edge detection by artificial neural networks has been discussed by Brännbacka [4], without going into details.

There are various modern computational methods available, as a support in image analysis. A selection of commercial and non-commercial tools is presented in Table 7.

6. Conclusions

There are numerous techniques originating in artificial intelligence that can be used in automatic image analysis (IA). This concerns especially artificial neural networks, machine learning and certain advanced statistical methods of data preparation and analysis. The reception of all these techniques in materials science is still very limited, even more so it is in case of testing concrete and similar composite materials.

The starting point for application of any artificial intelligence method in IA, applied to structural investigations of materials, seems to be a properly formatted database constructed from the direct results of the computer based image processing. Such database, to be used in the supervised learning, must be completed by information external to the image, e.g. from the human operator, that is from an expert. Most probably the database will be based on the binary representation of the image, but the information from high-level analysis of numerical images, e.g. by wavelets, seems to be really promising. Because of limited knowledge of the relations between the structure and various properties of concrete materials it seems too early yet to consider seriously the direct employment of ANNs in similar analysis, like it brought a success in medical radiology.

In two-dimensional representations of concrete materials the results of numerical image transformations (shades of grey image transformations) are often not very obvious to the investigator. Using advanced automatic image analysers the analysis can be done consciously or subconsciously (applying some heuristic argumentation) by shape descriptions, binary image convexity, values of distance functions, etc. The evaluation of the efficiency of a certain transformation results then often only from the previous experience.

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However, all such information can be processed with help of automated procedures, e.g. of machine learning.

Automatic feedback from the binary representation analysis to the level of numerical image processing seems possible, but so far such feedback was very little reported. It can follow the lines of the procedure suggested in Fig. 6.

In general AI can be of assistance:

- in case when there is knowledge hidden in examples, i.e. in a certain subset of records (instances, cases), originating in automatic image analysis, of certain sort, to be analyzed against the counter examples in another subset of records of another sort; discrimination of different sorts mentioned is external to the image, i.e. it is an information from the outside of the database; this is the field of possible application of machine learning techniques;
- in case when there is a hidden model of a certain phenomenon characterized by interrelation between numerical variables; this is the field of possible application of artificial neural networks.

Additionally, statistical methods of structure recognition can and should assist in appropriate database configuration, in ordering the attributes, selecting more appropriate derived attributes, helping in tuning of the parameters of the ANNs. In the latter case genetic algorithms techniques may be applicable. All these concepts belong to the so called '*soft methods*', closely related to artificial intelligence.

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