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KNOWLEDGE ACQUISITION FOR ADAPTIVE CONTROL OF THE EDM PROCESS

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Abstract
The problem of adaptive control of a EDM sinking machining is discussed in this paper. A way to alleviate the problem of slowness and instability of the eroding process is to use a suitable automatic adaptive control. In most EDM machines, the eroding process is adaptively controlled by the operator. He makes use of his skill and experience in order to satisfy the diversity of the requirements related to different working pieces. Sometimes, the operator supplements the strategy of his own with instructions from the process engineer. Hence the entire process control problem tends to be solved at the level of the human judgment. Consequently, people who are able to control the EDM process are an indispensable resource, and their experience has considerable value. Therefore, in this paper we study the possibilities of acquiring the existing knowledge regarding the EDM process with the aim of adaptively controlling the process automatically. Furthermore we designed an automatic controller for the EDM process. Three approaches to the synthesis of the controller strategy have been applied and the performance of each adaptive control strategy has been evaluated. Additionally, the future directions of implementation of knowledge acquisition techniques for the purpose of EDM process control is outlined.

Key Words
EDM, adaptive control, knowledge acquisition, artificial intelligence, cloning

1. INTRODUCTION

The EDM process is well established for manufacturing of forging and cast dies and injection molds. Since most of the work pieces are expensive, it is very important that the removal process is reliable, especially with regard to achieving the final shape accuracy and surface quality. This requirement is very demanding from the point of view of the EDM removal process, because it is random and unstable, especially under finishing regimes. Instabilities can be avoided by the choice of stable process parameters set. Unfortunately, efficiency and stability are mutually exclusive; therefore it is not possible to guarantee both of them in the long term. If efficiency is needed, then adaptive control of the process must be applied. Adaptive control of most EDM machines is performed by the operator and his strategy is one of possible sources for EDM-process control knowledge acquisition. Another source is the process engineer's experience and the appropriate technology database. In both cases, available knowledge is mainly expressed in descriptive, non-numeric and non-symbolic form. Therefore, the automatic controller must be designed in a way that will enable it to be flexible enough to interface easily with the process and with the human reasoning and his decision-making. Knowledge acquisition is an overall issue in manufacturig. The application of knowledge based systems was already investigated [1,2]. In these applications the appropriate knowledge acquisition has remained unsolved mainly because of insufficient expert knowledge elicitation.
To overcome discrepancies in knowledge representation between knowledge sources and automatic process control we used AI methods such as operator's control cloning. This methods are founded on methods of inductive learning from examples [3].

2. CONTROLLER CONFIGURATION

The controller is designed as a feedback system. It monitors the quality of discharge at the process output, and consequently, changes the process parameters at the process input. The feed-back transfer function is defined by the strategy expressed in terms of IF-THEN rules. Such a software control strategy is very flexible and it's advantages have already been confirmed in fuzzy controllers of AGIE EDM sinking machines [4].

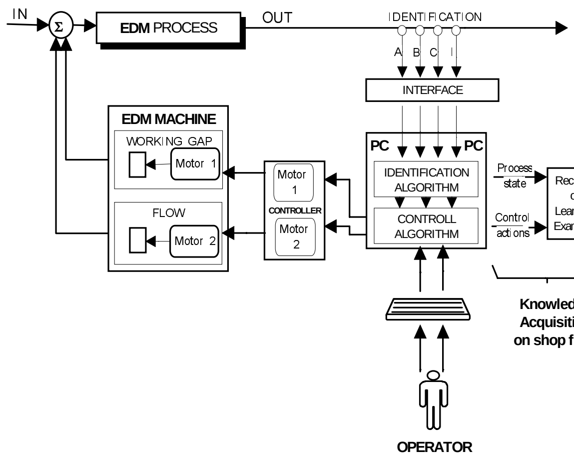

Fig. 1.: EDM sinking adaptive control.

Process Identification:
An external electronic unit is used to classify the EDM discharges in four qualitative categories: open voltage, effective, arcing and short circuit pulses. The state of the process (identificated attributes) is by the use of A/D converter, transmitted to the computer, specifically to the algorithm for decision making.

Decision making:
The decision making algorithm takes actions based on the identificated state of the process. The decision making algorithm is a set of IF-THEN rules which represent the control strategy. The process state attributes always appears in the conditional part of an IF-THEN rule, whereas the control action is defined in the consequence portion of the rule.

Control of the process parameters:
An increase or decrease of the gap is the control action which has the strongest influence on the process. It acts directly on the workspace and provokes a drastic response in the process performance. A considerable response is also achieved by changing the dielectric flow.

3. APPROACHES TO KNOWLEDGE ACQUISITION

Three different approaches to knowledge acquisition have been tried. In all cases, the chief source of information was the human interpretation of the control strategy.
The most important approach is to take advantage of the operator's knowledge and skill regarding adaptive control [5]. For that purpose, two different controller's strategies have been summarized: the first from the operator's verbal interpretation of the control strategy and the second by means of inductive learning from examples [3].

Operator's interpretation of the control strategy:
The most direct approach to the design of a control strategy is to translate the operator's verbal description in the form of IF-THEN rules. However such an approach represents two main difficulties [6]:
1. The difference between the form of verbal description and the resulting set of IF-THEN rules is remarkable. Namely, the operator does not make use of statistics for process evaluation; therefore, we use them in order to try to come closer to the attributes that are actually used by the operator. The latter are essentially qualitative in nature and are quite difficult to be reproduced numerically.
2. In addition, there is also a difference between what operator says he do and what he actually do [5]. Manual control is relatively intuitive and reflexive, and is, therefore, difficult to interpret verbally.
We avoided these problems somewhat by using *cloning approach* in order to capture operators knowledge.

Cloning approach:
This approach partly bridges the problem of interpretation of the operators control actions as well as translation of the operator's knowledge in symbolic form. By inductive learning it is possible to derive the control strategy from the records of learning examples [7]. We used the system FORS [3], which finds the relationship between the process state and the control action using records of operator's control demonstration (records of process state and operator's control actions represented in a numerical way).

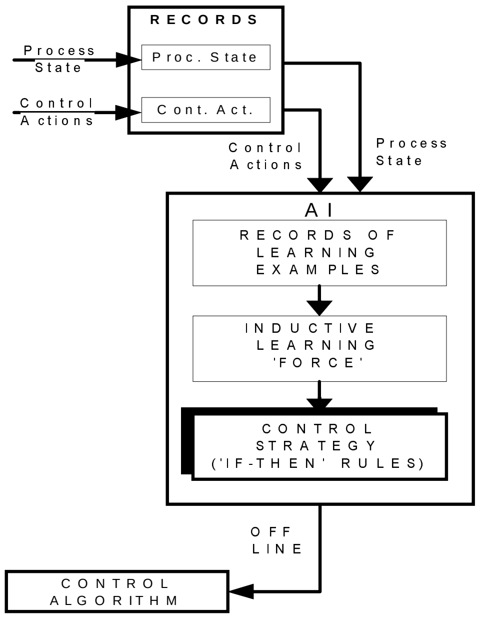

Fig.3.: System for inductive learning of the control strategy

The result of processing of a set of examples obtained from the operator's demonstration is as follows:

Rule for dielectric flow:
if $\mathrm{std}(A_{(t_i)})^{3s} > 0.3$ *then begin*
if $\mathrm{std}(A_{(t_i)})^{20s} > 2.5$ *then begin*
if $(\mathrm{avg}(A_{(t_i)})^{3s} < \mathrm{avg}(A_{(t_i)})^{20s})$ *and*
$(\mathrm{std}(I_{(t_i)})^{3s} < \mathrm{std}(I_{(t_i)})^{20s})$ *and*
$(\mathrm{std}(B_{(t_i)})^{3s} < \mathrm{std}(B_{(t_i)})^{20s})$ *then flow:=flow+0.1*
else begin
if $\mathrm{avg}(B_{(t_i)})^{20s} < \mathrm{avg}(B_{(t_i)})^{3s}$ *then flow:=flow+0.5;*
else flow:=flow+0.1
end;
end;
end;

Rule for the size of the working gap:
if $\mathrm{std}(I_{(t_i)})^{20s} >= 0.55$ *then gap:=gap+0.3 else begin*
if $\mathrm{avg}(C_{(t_i)})^{20s} >= 12.7$ *then gap:=gap+0.7 else begin*
if $\mathrm{avg}(B_{(t_i)})^{3s} <= 55.5$ *then gap:=gap-0.2 else gap:=gap-0.5*
end;
end;

$\mathrm{std}(X_{(t_i)})^{y}$ ....standard deviation of 'X-type' pulses portion during 'y' seconds time interval

$\mathrm{avg}(X_{(t_i)})^{y}$ .... average amount of 'X-type' pulses portion during 'y' seconds time interval

$\mathrm{std}(I_{(t_i)})^{y}$ .... standard deviation of average electric current during 'y' seconds time interval

X= ....A (open voltage discharge), B (working discharges), C (acing discharges)
y= ....3 seconds time interval, 20 seconds time interval

A general advantage of the control strategy is that it is comprehensible. Such a strategy is easy to survey and extend with new rules. The strategy resulting from inductive learning method we used is able to control the process but is not comprehensible.

Control strategy derived from engineer's knowledge regarding the EDM-sinking process:
Basic actions of the controller can be obtained from deep knowledge of the EDM process such as process engineer's knowledge. An example of engineers reasoning in terms of EDM-process control is as follows:

> *The main requirement of the control strategy is to avoid a destructive effect of the C (arc) impulses. When the amount of C impulses in the process starts to increase, it is necessary to clean the working gap of the products of the process as soon as possible. The best effect is achieved by increasing the working gap, while a similar, but slightly weaker effect is achieved by increasing the wash flow. These two control actions are intended to stabilize the process and, at the same time, protect the surfaces from damage. They are expressed by the rules presented below. An effective machining is achieved in all other process states by decreasing the working gap and dielectric flow, which are opposite actions to those needed for stabilization. They occur in the ELSE part of the rule.*

The deduced algorithm is:
Rule for the wash flow:
if $\mathrm{avg}(C_{(t_i)})^{3s} > 7.5$ *then flow:=flow+1*
else flow:=flow-0.5;

Rule for the size of the working gap:
if $\mathrm{avg}(C_{(t_i)})^{3s} > 10$ *then gap:=gap+1*
else gap:=gap-0.5

The simplicity and clarity of the strategy are remarkable advantages of such a knowledge acquisition approach. Furthermore the resulting controller's performance is very good in the speed of response to changes in the process as well as in achieving process intensity.

4. RESULTS

All three versions of the controller were tested by means of experimental runs in risky conditions (finishing regime with bad flushing conditions).
All three controllers succeeded in controlling the process without causing unrecoverable damage on the surface of the working piece. This was quite successful considering the severe working conditions.
The next criterion taken into account was the efficiency of the machining. The controller obtained with *cloning approach* and the one obtained with the strategy based on *engineer's knowledge of the EDM process* turned out to be the most efficient. The strategy obtained from *the operator's interpretation of the control strategy* was not able to achieve efficient machining although it prevented the process from unrecoverable performance degradation quite satisfactory.
Another criterion of controller evaluation is to estimate its stability. However, this could hardly be done for the controller obtained from the *operator's interpretation of the control strategy*, since it operates far from risky processing conditions. The controller derived by the strategy based on *engineer's knowledge* turned out to be the most stable, owing to the quick and efficient stabilizing reactions to undesirable process performance. Contrary to that, the controller obtained by *cloning approach* is less stable because the control actions are too undecided and smooth. What are actually lacking are drastic stabilization actions.

CONCLUSIONS

Most realistic processes are so complex that it is very difficult to build good models of them. It is, therefore, important to make use of as much of the existing knowledge of the process as possible. Expert experience and engineering insight into the technology of the machine are most often available and already exploited for EDM control purposes with remarkable benefit [4]. However, it happens that a great deal of existing knowledge is rejected due to the form in which it is expressed and lack of on line knowledge acquisition on shop floor. Hopefully, with advances in the knowledge acquisition methods, new opportunities may appear that will help fill the gap between human interpretation of expertise and its symbolic and numeric form in automatic systems.
In this study we elaborated upon the possibilities acquiring different types of human knowledge for the control of EDM processes. All approaches turned out to be successful. In order to increase their practical applicability, it is necessary to remove the drawbacks which were observed during experimental runs. From the results obtained, it seems promising and reasonable to direct future research towards the integration of control strategies obtained from different knowledge sources.

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