A reinforced iterative formalism to learn from human errors and uncertainty

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ABSTRACT

This paper proposes a reinforced iterative formalism to learn from intentional human errors called barrier removal and from uncertainty on human-error parameters. Barrier removal consists in misusing a safety barrier that human operators are supposed to respect. The iterative learning formalism is based on human action formalism that interprets the barrier removal in terms of consequences, i.e. benefits, costs and potential dangers or deficits. Two functions are required: the similarity function to search a known case closed to the input case for which the human action has to be predicted and a reinforcement function to reinforce links between similar known cases. This reinforced iterative formalism is applied to a railway simulation from which the prediction of barrier removal is based on subjective data.

1. Introduction

The main concept of an iterative learning approach consists in detecting and minimizing tracking errors with an initial low level of knowledge on the possible action consequences (Lee et al., 2000; Xu et al., 2004; Xu and Yan, 2004; Chien and Yao, 2004; Norrlöf and Gunnarsson, 2005). The corresponding algorithm adjusts the learning parameters in order to reduce errors between an input signal and an output one after a limited number of iterations. The tasks usually relate to repetitive activities such as robot movements.

Two main classes of iterative-learning control schemes can be identified. The first class concerns the frequency-based approaches:

- The feedforward-feedback scheme (Lee et al., 2000) or the previous cycle-learning scheme (Xu et al., 2004) consists of using the previous iterations to calculate the current one.
- The current cycle-learning scheme (Xu et al., 2004) or the direct adaptive scheme (Wang et al., 2004) consists in integrating the previous iterations and the current error to assess the current input signal.

This first class of approaches can be combined with the second class concerning the time-based approaches (Norrlöf and Gunnarsson, 2005):

- The causal scheme consists in integrating the historical signal evolution of the previous iteration to assess the current one.
- The non-causal scheme consists in taking into account both the historical and the future signal evolution of the previous iteration to assess the current one.

Disturbances and noises may perturb signal identification and assessment. Iterative learning approach can take into account such effects on output signals (Chien and Yao, 2004; Mahmoud, 2004; Tayebi, 2004). These effects are then interpreted in terms of uncertainty.

This paper develops a formalism based on the iterative-learning control principles to predict human barrier removals. The input signals related to the explanation of the occurrence or the non-occurrence of a barrier-removal errors are interpreted using the so-called BCD model (Polet et al., 2002, 2003; Vanderhaegen, 2004), i.e., in terms of Benefits, Costs and potential Dangers or Deficits. Benefits and costs occur immediately when the human behavior is successful, whereas the potential dangers or deficits occur when it fails.

The proposed iterative learning formalism does not aim at reducing these differences (e.g. to make the tracking error converge to zero after an infinite number of iterations), but at using the uncertainty on their assessments to improve the action prediction process. It is a direct adaptive and error-tolerant...
2. The reinforced iterative approach

For a given iteration of data processing, the correct prediction assessment consists in comparing the real observed decision noted $u_i$ with the predicted one noted $u'_i$ given by a reinforced iterative learning tool, Fig. 1. It is based on input data vectors noted $e_i$ and the previous iterations that are modelled by the previous input vectors and their associated decisions ($e_{i-1}, u_{i-1}$).

A vector $e_i$ contains a series of triplets $(b_e, c_e, d_e)$ for a given criterion $k$. For each iteration, the vector contains the same number of data related to $m$ criteria: $(b_e, c_e, d_e, b_{e2}, d_{e2}, ..., b_{em}, c_{em}, d_{em})$. Each parameter is defined into an interval of values noted $\Omega = [X_{\min}, X_{\max}]$ and the output signal $u$ is defined into an interval of values noted $\Psi = [0, 1]$.

This system requires a similarity function noted $S$ that identifies, into the knowledge or database noted $E_i$, the vector $(e, u)$ noted $(e_i, u_i)$ for which $e$ is similar to the input vector $e_i$. The database $E_i$ is modified regarding a reinforcement function noted $R$ to handle the database content, Fig. 2.

To simplify the explanation of the process, functions that have the same purpose, but different number or type of parameters have the same name (i.e. the $S$ and $R$ functions).

The function $S$ finds a possible input signal $u$ regarding the input vector $e_i$ and knowing all the previous vectors $(e, u)$ of $E_i$ obtained from the previous iterations. The Euclidean distance value is used to find the vector $e'$:

$$S : \Omega^m \times \Psi \rightarrow \Psi$$

$$e_i \mapsto u'_i = S(e_i) = u'/(e \cup u) \cap u'$$

$$= u.\forall e_i \in E_i, \| (e_i)^T - (e')^T \| = \min \| (e_i)^T - (e')^T \|$$

When a vector $e$ is found, its corresponding decision $u$ is considered as the prediction of $u_i$ noted $u'_i$.

Then, the function $S$ is found and integrates other parameters. It aims at finding the vector $(e_{i-1}^+, u_{i-1}^+)$, noted $(e_{i-1}^+, u_{i-1}^+)$ that correspond to the vector $(e_i, u_i)$ of $E_i$ with the minimum differences between the parameters of the vector $(e_{i-1}, u_{i-1})$:

$$S : \Omega^m \times \Psi \rightarrow \Omega^m \times \Psi$$

$$(e_{i-1}, u_{i-1}) \mapsto (e_{i-1}^+, u_{i-1}^+) = S(e_{i-1}, u_{i-1}),$$

$$\forall (e_i, u_i) \in E_i, \| (e_{i-1}, u_{i-1}) - (e_{i-1}^+, u_{i-1}^+) \|^2$$

$$= \min \| (e_{i-1}, u_{i-1}) - (e_{i-1}^+, u_{i-1}^+) \|^2$$

The obtained error $\varepsilon_1$ is then processed by the function $R$ in order to reinforce the impact of the occurrence of the vector $(e_{i-1}, u_{i-1})$, handling the weight parameters related to the vector $(e_{i-1}, u_{i-1})$ with a predefined function $\Delta$ that allocates a weight regarding the value $\varepsilon_1$, Fig. 3.

$$R : \Omega^m \times \Psi \rightarrow \Omega^m \times \Psi$$

$$(e_{i-1}^-, u_{i-1}^-) \mapsto (e_{i-1}^+, u_{i-1}^+) = R(e_{i-1}^-, u_{i-1}^-),$$

$$(e_{i-1}^-, u_{i-1}^-)^T = (e_{i-1}^+, u_{i-1}^+)^T + \Delta[(e_{i-1}, u_{i-1})^T - (e_{i-1}, u_{i-1})^T]$$

The error $\varepsilon_1$ is equal to

$$\varepsilon_1 = (e_{i-1}, u_{i-1})^T - (e_{i-1}^+, u_{i-1}^+)^T$$

In a second step, the errors $\varepsilon_2$ between the vectors $(e, u) \neq (e_{i}^+, u_{i-1}^+)$ of $E_i$ and the reinforced one $(e_{i}^+, u_{i-1}^+)$ are processed with the function $R$ in order to obtain a new database based on the new vectors $(e', u') = R(e, u)$ and $(e_{i}^+, u_{i-1}^+)$.

$$R : \Omega^m \times \Psi \rightarrow \Omega^m \times \Psi$$

$$(e, u) \mapsto (e', u') = R(e, u), \forall (e, u) \neq (e_{i}^+, u_{i-1}^+), (e', u')$$

$$= (e, u) + \Delta[(e_{i}^+, u_{i-1}^+)^T - (e, u)^T]$$

The error $\varepsilon_2$ is then equal to

$$\varepsilon_2 = (e_{i}^+, u_{i-1}^+)^T - (e, u)^T$$

<table>
<thead>
<tr>
<th>Correct prediction assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_i$</td>
</tr>
<tr>
<td>$u'_i$</td>
</tr>
<tr>
<td>$u_{i+1}$</td>
</tr>
<tr>
<td>$u'_{i+1}$</td>
</tr>
<tr>
<td>$e_i \rightarrow$ Iteration $i$ $\rightarrow$</td>
</tr>
<tr>
<td>$e_{i+1}, u_{i+1}$</td>
</tr>
<tr>
<td>$e', u'$</td>
</tr>
</tbody>
</table>

Fig. 1. The prediction process statement.

Fig. 2. The iterative learning formalism based on the BCD parameters.

Fig. 3. Allocation of a weight $\Delta(e)$ regarding an error value $\varepsilon$. |
The obtained vectors \((e_i, u^*)_i\) and the vector \((e_{i+1}, u_{i+1}^*)_1\) are gathered into a new database noted \(E^X_i\) that replaces \(E_i\).

\[
E^X_i = ((e^X_i, u^*_i) | (e^X_{i-1, 1}, u^*_{i-1, 1})) \quad (e^X_i, u^*_i) = R(e_i, u_i) \cup (e^X_{i-1, 1}, u^*_{i-1, 1})
\]

### 3. The uncertainty-based learning function

The uncertainty values integrated into the iterative learning process consists in taking into account a vector \(n_i\) of uncertainty on the parameters of \(e_i\) and in creating new relations between \(e, n_i\) and \(u_i\).

For each criterion of a given iteration, the uncertainty vector \(n_i\) contains \((\{1, \beta_1, \gamma_1, \beta_2, \gamma_2, \ldots, \beta_m, \gamma_m\}\) and relates to the certainty value on the \((b_1, c_1, d_1, c_2, d_2, \ldots, b_m, c_m, d_m)\) parameters, respectively, of the vector \(e_i\).

The prediction and the learning processes require the information of the vector \(n_i\), Fig. 4.

Here again, in order to simplify the explanation of the process, functions that have the same purpose but different number or type of parameters have the same name (i.e. the \(S, R\) and \(T\) functions).

The prediction process uses the input vector \((e_i, n_i)\) noted \((e_i, n_i)\) to determine \(u^*_i\) regarding the similarity-based assessment presented previously. The learning process duplicates the input vector \((e^X_{i-1, 1}, u^*_{i-1, 1})\) noted \((e^X_{i-1, 1}, u^*_{i-1, 1})\) the vector \((e^X_{i-1, 1}, u^*_{i-1, 1})\) containing the vectors \((e^*_{i-1, 1}, u^*_{i-1, 1})\) noted \((e^*_{i-1, 1}, u^*_{i-1, 1})\).

Each value of \(n_i\) is defined into the set \(\Phi\) that contains one of the three values \((\text{Low}, \text{Moderated}, \text{High})\). \(\text{Low}, \text{Moderated}\) or \(\text{High}\) mean, respectively a low, moderated or high level of certainty on the BCD parameters. A couple noted \((x, y)\) from a vector \((e_i, n_i)\) relates to the value \(y\) of \(n_i\) of certainty on the parameter \(x\) of \(e_i\). The couple \((x, y)\) relates to the same criterion. The transformation of the input vector \((e_i, n_i)\) by the function \(T\) consists in replacing the values of \(n_i\) as follows:

\[
T: \Omega^2 \times \Phi^2 \rightarrow \Omega^2 \times \Psi^2
\]

\[
(e_i, n_i) \mapsto (e^*, n^-) \quad \forall (x, y) \in (e_i, n_i), x = e_i, y = n_i, n^- = \bigcup_{j=1}^{m} T(x, y)
\]

### Fig. 4. Iterative learning formalism based on uncertainty allocated to BCD parameters.

The result of the function \(T(x, y)\) depends on the value of \(y\)

\[
\begin{align*}
T: \Omega \times \Phi &\rightarrow \Psi \\
(x, y) &\mapsto \begin{cases} 
Z = T_L(X) & y = \text{Low} \\
Z = T_M(X) & y = \text{Moderated} \\
Z = T_H(X) & \text{otherwise}
\end{cases}
\end{align*}
\]

Examples of the functions \(T_L, T_M\) and \(T_H\) are given on Fig. 5.

The second step consists in predicting the output signal \(u^*_i\) with the similarity function \(S\):

\[
S: \Omega^2 \times \Phi^2 \rightarrow \Psi
\]

\[
\begin{align*}
e^* &= e, \\
\forall (e_i, n_i) \in (e_i, n_i), x = e_i, y = n_i, n^- = \bigcup_{j=1}^{m} T(x, y)
\end{align*}
\]

### Fig. 5. Examples of uncertainty-based learning functions.

\[
\begin{align*}
e^* &= e, \\
\forall (e_i, n_i) \in (e_i, n_i), x = e_i, y = n_i, n^- = \bigcup_{j=1}^{m} T(x, y)
\end{align*}
\]

Regarding all the obtained duplicated vectors from the previous iteration \((e^-_i, n^-, u^-)\) from the database \(E^-_{i-1}\), the function \(S\) researches the vector \((e^+_{i-1}, n^+_{i-1}, u^+_{i-1})\) from the database \(E^+_i\) that is similar to each vector \((e^*_i, n^-, u^-)\)

\[
S: \Omega^2 \times \Phi^2 \rightarrow \Omega^2 \times \Psi
\]

\[
(e^-_i, n^-, u^-) \mapsto (e^+_{i-1}, n^+_{i-1}, u^+_{i-1}) = S(e^*_i, n^-, u^-), \\
\forall (e_k, n_k, u_k) \in E_i, (e^*_i, n^-, u^-) \mapsto (e^+_{i-1}, n^+_{i-1}, u^+_{i-1})
\]

The function \(R\) is adapted in order to reinforce the found vector \((e^+_{i-1}, n^+_{i-1}, u^+_{i-1})\)

\[
R: \Omega^2 \times \Phi^2 \rightarrow \Omega^2 \times \Psi
\]

\[
(e^+_{i-1}, n^+_{i-1}, u^+_{i-1}) \mapsto (e^+_{i-1}, n^+_{i-1}, u^+_{i-1}) = D(e^+_1, n^+_{i-1}, u^+_{i-1})
\]

where \(e_k\) is a value related to the \(k\)th criterion of the vector \(e_i\) and \(n_k\) a value related to the \(k\)th criterion of the vector of uncertainty \(n_i\).
The error $e_1$ is then equal to

$$e_1 = (e_{i-1}, n_{i-1}, u_{i-1})^T - (e_i, n_i, u_i)^T.$$

The function $R$ to reinforce the database of known cases is adapted as follows:

$$R : \Omega_{1m} \times \Psi_{1m} \times \Psi \to \Omega_{3m} \times y^{3m} \times \Psi$$

$$(e, n, u) \mapsto (e^1, n^1, u^1), \forall(e, n, u) \neq (e^2, n^2, u^2), (e^3, n^3, u^3)$$

$$= (e, n, u) + \Delta((e_{i-1}, n_{i-1}, u_{i-1})^T - (e, n, u)^T).$$

The error $e_2$ is then equal to

$$e_2 = (e_{i-1}, n_{i-1}, u_{i-1})^T - (e, n, u)^T.$$

The proposed reinforced iterative formalism was implemented into a neural network system based on the Kohonen model (Kohonen, 2001; Neuhauxs and Bunke, 2005). This implementation is detailed in Zhang et al. (2004). The network contains a limited number of neurons that integrate progressively the vectors $(e, u)$ of the previous iterations. Initially, the weight parameters of each neuron are initialized by stochastic values that are modified by using the functions $S$ and $R$ to integrate the values of the vectors $(e, u)$. The formalism was then tested with the data obtained on a railway simulation.

### 4. Example of application

This application consists in predicting particular human action called barrier removal. A barrier removal is an intentional violation related to a non-respect of a rule or a deactivation of a technical system, whereas this rule and this technical system were designed to protect the controlled system from the occurrence or the consequences of an undesirable event such as an accident (Vanderhaegen, 2004). The proposed study applies the so-called TRANSPAL platform that proposes a series of barriers that can be removed (Polet et al., 2004; Polet and Vanderhaegen, 2007). It consists in controlling trains from a departure depot to an arrival one, crossing and stopping at transformation areas on which human operators have the possibility to operate on the products located into the stopped trains (Zhang et al., 2004), Fig. 6.

In order to limit risks of miss-control, several technical barriers are proposed in order to control the traffic flow, the routes of the trains, to prevent collisions or derailment, and to inform operators at transformation areas. There are 45 signals with which human controllers have to interact:

- Signals to prevent traffic problems related to the inputs and the outputs of trains from depots.
- Signals to prevent traffic problems into transformation areas: they are signals to control inputs and outputs at the transformation areas and delays to inform that the processing of the content of a train is in course.
- Signals to prevent traffic problem at the shunting device.

Human controllers can only act on the position of the switch points, the state of the signals, the announcement of traffic flow at transformation areas. They used TRANSPAL during two experiments: the first one integrates all the technical barriers that are signals at depot, at switching device, at transformation area and the second one proposes to the human operators the possibility to remove some of these technical barriers.

TRANSPAL provides human controllers with interface to control train movements by managing the shunting devices and the stop barriers by achieving four distinguished criteria:

- The traffic safety in terms of collision or derailment.
- The quality related to the respect of the timetable.
- The production related to the respect of the stops at the stations.
- The human workload related to the occupational rate.

Twenty human operators have achieved several experiments on which they have the possibility to remove some stop barriers and to interpret these actions of barrier removals in terms of benefits, costs and potential deficits and to associate a degree of uncertainty on these benefits, costs and potential deficits, for each criterion.

The purpose of the application of the learning function is to predict the barrier removals (e.g., the input signal $u_i$) regarding subjective values on the corresponding benefits, costs and deficits.

![Fig. 6. The TRANSPAL simulation interface.](image-url)
for each objective (e.g., the couple of vectors \((e_i, n_i)\)) and knowing all the previous relations between the occurred barrier removals and their corresponding subjective assessments in terms of benefits, costs and potential deficits (e.g., the triplets \((e_0, n_0, u_0), (e_1, n_1, u_1), \ldots, (e_i, n_i, u_i)\)).

Without incertitude on the parameters BCD, the neural network learning phase requires:

- The subjective and qualitative values of the benefit, the cost and the potential deficit associated to the barrier removal for each criterion (i.e. \(e_0, e_1, \ldots\)).
- The human action parameter related to the respect or the removal of the corresponding barrier (i.e. \(u_0, u_1, \ldots\)).

With the incertitude on the parameters BCD, the neural network learning phase requires the following triplets:

- The subjective and qualitative values of the benefit, the cost and the potential deficit associated to the barrier removal for each criterion (i.e. \(e_0, e_1, \ldots\)).
- The subjective and qualitative values of certainty on these evaluations (i.e. \(n_0, n_1, \ldots\)).
- The human action parameter related to the respect or the removal of the corresponding barrier (i.e. \(u_0, u_1, \ldots\)).

Each subjective evaluation of the benefits, the costs and the potential deficits is included into the interval \([1, 5]\): the lower the value is, the less important the corresponding benefit, cost or potential deficit is.

The three possible values of the initial subjective uncertainty assessment are: low, moderated or high. Regarding these values, the associated uncertainty-based learning functions \(T_L, T_M\) and \(T_H\) are given on Fig. 7.

Fig. 8 gives an example of the results related to the prediction quality of the neural network.

The 5th iteration corresponds to the learning phase integrating the data of five human operators and the prediction is assessed for the other 15 operators, i.e., the learning process is stopped when \(i = 4\) in order to take into account the data of five human operators and the prediction of \(u_i^C\) consists in predicting consecutively the inputs for the other ones. The 16th iteration contains the data of 16 human operators and the prediction phase concerns the last 4 human operators, i.e., the learning process is stopped when \(i = 15\) related to the data of 16 human operators and the prediction of \(u_i^C\) consists in predicting consecutively the inputs for the other ones.

The prediction rate is a comparison between the prediction given by the neural network and the real behavior of the human operators. Results show that the number of scenarios used for the learning phase has an impact on the convergence of the prediction rate. The prediction rate converges toward 85% without using the
uncertainty based data, whereas it converges toward 95% when the evaluation and the transformation of subjective and qualitative uncertainty levels are used.

5. Conclusion

This paper has developed an original reinforced iterative formalism to learn from human errors and uncertainty. This human error is interpreted in terms of benefits, costs and potential deficits, and the uncertainty concerns the uncertainty on these parameter assessments, i.e. the uncertainty on the benefits, the costs and the potential deficits of a given human error. The proposed formalism is used in order to predict the output signal at a given iteration regarding the human error parameters and their uncertainty levels of this iteration and the data of the previous iterations. The approach is applied to a railway transport simulation for which human operators have to assess subjectively their own erroneous action in terms of benefits, costs and potential deficits on four distinguished criteria. The use of subjective uncertainty on these assessments has increased the number of possible scenarios of human action occurrence. It has also refined the prediction quality.

Perspectives for this formalism consist in assessing the relevance of the uncertainty in relation to used criteria. Some criteria could, thus, be dismissed due to an uncertainty that may be assimilated to some noise in both the neural network and the iterative learning control. Interest of the formalism is related to the determination of a minimal set of criteria likely to produce an optimal rate of correct prediction. The idea is to provide the proposed iterative learning control with different combinations of the input vectors. The determination of an optimal subset is highly interesting in terms of computation time to allow an online prediction of the human error by having the iterative learning control directly connected to a real transport system.

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