Human Expertise in Fault Detection and Adjustment An Empirical Case Study

Rainer Knauf

Technical University of Ilmenau School of Computer Science and Automation *Ilmenau, Germany*

Setsuo Tsuruta

Tokyo Denki University School of Information Environment *Tokyo, Japan*

Avelino J.Gonzalez

University of Central Florida Dept. of Electrical and Computer Engineering *Orlando, FL, USA*

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1. System Evaluation and Refinement – An Issue of this WG?

- Today's opportunities to design and employ complex systems rise the question, whether or not we are able to control what we are able to build
- The impact of invalidity increases with the with the number today's systems' application fields and their sensibility to malfunctions
- Today's IT-systems may become a real threat without ensuring their validity
- Moreover, many interesting applications are characterized by some dynamics in their topical background.
- Thus, these systems need to be refined based on both, revealed invalidities and new topical insights.
- In fact, these concerns are issues of <u>dependable computing</u>.
- Maybe they are not an issue of fault tolerance, but of <u>fault detection</u> and adjustment instead.

Verification, validation, and refinement – what's it?



Humans in the loop – a problem?

Yes, indeed! But is there any alternative ?

2. Our Conceept – An Overview

Step # 1: Test case generation

Generate and optimize a set of test cases [*test data* , *expected output*] that meets the competing requirements (1) **coverage** and (2) **efficiency**

Step # 2: Test case experimentation

Exercise the test data by both the system under investigation and a panel of validating experts as a TURING Test - like experiment

Step # 3: Evaluation

Interpret experimentation results & report test case associated invalidities

Step # 4: Validity assessment

Analyze reported results and conclude validity assessments associated with (1) test cases, (2) outputs, (3) rules, and (4) the entire system

Step # 5: System refinement

Formally reconstructing the rule base so that it infers best rated solutions

3 The Problem with Human Experience

What's the problem with employing human expertise for system validation?

- ☺ Experts have different beliefs, experiences and learning capabilities.
- ☺ Experts are not free of mistakes.
- ☺ Experts' opinions about the desired system's behavior
 - differ from each other
 - change over time as a result of misinterpretations, mistakes or new insights
- Experts are often too busy and/or too expensive to hire them for system validation and refinement.



The Involvement of Humans so far

Where is the human input into our validation technology?



QuEST Quasi Exhaustive Set of Test Cases

- a well-designed set that ensures coverage by formally analyzing the input space
- *ReST* <u>**Re**asonable</u> <u>**S**</u>et of <u>**T**</u>est Cases
 - a subset of QuEST that ensures the requirement efficiency by using validation criteria

Objectives of modeling human experience

Supplementing additional expertise to the validation panel, in particular:

- Suggesting new solutions to test cases, different from the panel's suggestions
- Offering additional input without consulting humans
- Substituting missing individual human expertise
- > ... others ∉ this talk

4 Incorporating a Validation Knowledge Base (VKB) as a Model of Collective Experience

4.1 The Content of VKB

All formal and informal data that can be collected, i.e. to each test case

- the (input) test data t_j
- a list of all solvers E_{Kj}
- > a list of all raters E_{II}
- associated optimal (best rated) solution sol_{Ki}^{opt}
- > the ratings provided by the rating experts r_{IJK}
- > the certainties of these ratings c_{IIK}
- > a session time stamp τ
- > an informal description of the context D_i

Thus, **VKB** is a set of 8-tuples $[t_i, E_{Ki}, E_{Ii}, sol_{Ki}^{opt}, r_{IiK}, c_{IiK}, \tau, D_i]$

A part of VKB in the prototype test experiment

 e_1, e_2, e_3 human experts $t_1, t_2, ...$ test case inputs $o_1, o_2, ...$ solutions (outputs)

τ

session #

r

rating: 1 for correct, 0 for incorrect

С

certainty: 1 for certain, 0 for uncertain

t_j	$E_{\it Kj}$	E _{Ij}	sol _{Kj} opt	r _{IjK}	c _{IjK}	τ	D_{j}			
<i>t</i> ₁	$[e_{l}, e_{3}]$	$[e_1, e_2, e_3]$	06	[1,0,1]	[0,1,1]	1				
<i>t</i> ₁	[e ₃]	$[e_{l}, e_{2}, e_{3}]$	04	[1,0,1]	[1,1,1]	3				
<i>t</i> ₁	[e ₂]	$[e_1, e_2, e_3]$	<i>0</i> ₁₇	[0,1,0]	[1,1,1]	4				
<i>t</i> ₂	$[e_{l}, e_{3}]$	$[e_{1}, e_{2}, e_{3}]$	<i>0</i> ₇	[0,0,1]	[0,0,1]	1				
<i>t</i> ₂	[e ₃]	$[e_1, e_2, e_3]$	<i>o</i> ₂	[1,0,1]	[1,1,1]	3				
<i>t</i> ₂	[]	$[e_{1}, e_{2}, e_{3}]$	<i>o</i> ₂	[1,0,1]	[1,1,1]	4				
<i>t</i> ₃	[e ₂]	$[e_{1}, e_{2}, e_{3}]$	0 ₂₀	[0,1,0]	[0,1,1]	1				
<i>t</i> ₄₂	$[e_{1}, e_{2}, e_{3}]$	$[e_{1}, e_{2}, e_{3}]$	0 ₂₃	[1,1,1]	[1,1,1]	2				
t ₄₂	$[e_{1}, e_{2}, e_{3}]$	$[e_{l}, e_{2}, e_{3}]$	0 ₂₃	[1,1,1]	[1,1,1]	3				

4.2 The Usage of VKB

External collective experience: $sol \in VKB$, but not provided by the panel



Quantifying the supplement of VKB to the human expertise

Set of external solutions (not provided by the current panel):

 $ExtSol := \{ sol: \exists Entry: Entry \in VKB, \Pi_{I}(Entry) \in \Pi_{I}(ReST), sol = \Pi_{A}(Entry) \}$

⇒ Workload reduction factor of the VKB

by skipping the solving process

workload reduction factor = | ExtSol | / | ReST |

⇒ Expertise gain factor of the VKB

by supplementing ReST with interesting solutions outside the panel's expertise

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expertise gain factor = |ReST| / (|ReST| - |ExtSol|)
```

5 Incorporating Validation Expert Software Agents (VESA) as Models of Individual Experiences

Objectives

- Forming a model of each validator's individual knowledge and behavior
- Successive refinement of this model by consecutive validation sessions

Source of VESA's knowledge: solving and rating results

the associated human origin

VESAs

- > are formed just in the moment of their need and "forgotten" after their usage
- model just the required aspect of their human origin based on historical information of former sessions (i.e. not the current session)
- > are requested in case its human counterpart is not available
- may be requested even if the human origin is present to validate the VESA concept itself by comparing the behavior of VESA with the real one of the human source.

VESA models the solving behavior of an expert \underline{e}_i for a test case \underline{t}_i as follows

Step # 1

In case e_i solved (*with a solution different from "unknown"*) t_j in a former session, his/her solution with the latest time stamp τ will be provided by **VESA**.

Step # 2

- ✓ All validators e^{i} , who ever delivered a solution to t_{j} form a set $Solver_{i}^{0}$, which is an initial dynamic agent for e_{i} : $Solver_{i}^{0} := \{e' : [t_{j}, E_{Kj}, ...] \in VKB \land e' \in E_{Kj}\}$
- ✓ Select the <u>most</u> similar expert e_{sim} with the largest set of cases that have been solved by both e_i and e_{sim} with the same solution in the same session. e_{sim} forms a refined dynamic agent $Solver_i^1$ for e_i : $Solver_i^1 := e_{sim} : (e_{sim} \in Solver_i^0) \land (|\{[t_i, E_{Ki}, ..., sol_{Ki}^{opt}, ..., ..., \tau, ...]: e_i \in E_{Ki}, e_{sim} \in E_{Ki}\}| \rightarrow max!)$
- ✓ Provide <u>the</u> latest solution of the expert e_{sim} to t_j , i.e. the solution with the latest time stamp τ by **VESA**.

Step # 3

If there is no such most similar expert, provide the solution sol := unknown by **VESA**.

An example of a VESA 's solving behavior compared to the human counterpart

EK^3

external knowledge (entries of the VKB) available in the 3rd session

e_2

human expert #2

*t*₁, *t*₂, ...

test case inputs

*o*₁, *o*₂, ...

solutions (outputs)

$VESA_2$

the VESA-model of expert #2

EV	soluti	on of	$\mathbf{F} \boldsymbol{V}$	solution of		
LA3	VESA ₂	<i>e</i> ₂	LA3	VESA ₂	e_2	
t ₂₉	08	08	t ₃₆	09	09	
<i>t</i> ₃₀	09	09	t ₃₇	09	09	
t ₃₁	<i>o</i> ₂	<i>o</i> ₂	t ₃₈	09	09	
t ₃₂	08	03	t ₃₉	09	09	
t ₃₃	08	08	t ₄₀	0 ₂₃	0 ₂₃	
t ₃₄	<i>o</i> ₂	<i>o</i> ₂	t ₄₁	0 ₁₉	0 ₂₂	
<i>t</i> ₃₅	08	08	t ₄₂	0 ₂₃	0 ₂₃	

VESA models the rating behavior of an expert \underline{e}_i for a test case \underline{t}_i as follows

Step # 1

In case e_i rated t_j in a former session, adopt the rating with the latest time stamp τ s and provide the same rating r and the same certainty c by **VESA**.

Step # 2

- ✓ All validators e^{i} , who ever delivered a rating to t_{j} form a set $Rater_{i}^{0}$, which is an initial dynamic agent for e_{i} : $Rater_{i}^{0} := \{e' : [t_{j}, _, E_{lj}, ...\} \in VKB \land e' \in E_{lj}\}$
- ✓ Select the most similar expert e_{sim} with the largest set of cases that have been rated by both e_i and e_{sim} with the same rating in the same session. e_{sim} forms a refined dynamic agent $Rater_i^1$ for e_i : $Rater^1 := e_{im} : (e_i \in Rater^0) \land (| ([t_i = E_i : sol^{opt} : r_i = \sigma_i)] \land (= E_i) \land (= E_i)$

 $Rater_i^1 := e_{sim} : (e_{sim} \in Rater_i^0) \land (|\{[t_j, _, E_{Ij}, sol_{Kj}^{opt}, r_{IjK}, _, \tau, _]: e_i \in E_{Ij}, e_{sim} \in E_{Ij}\}| \rightarrow \max!)$

✓ Provide the latest rating *r* of the expert e_{sim} along with its certainty *c*, i.e. the ones with the latest time stamp τ , to the present test case t_i by **VESA**.

Step # 3

If there is no such most similar expert, provide the rating r := norating along with a certainty c := 0 by **VESA**.

An example of a VESA 's rating behavior compared to the human counterpart

<i>EK</i> ³	EV	colution	rating	, of	FV	colution	rating of	
external	Er3	solution	VESA ₂	e_2	ER3	solution	VESA ₂	e_2
knowledge	t_1	04	0	0	t ₂₉	03	0	0
VKB) available in	t_1	06	0	0	t ₂₉	04	0	1
the 3 rd session	t_1	<i>o</i> ₂₁	0	0	t ₂₉	08	1	1
<i>e</i> ₂	t_1	<i>0</i> ₁₈	1	1	t ₂₉	0 ₁₆	0	0
human expert #2	t_2	<i>o</i> ₂	0	0	t ₃₀	<i>o</i> ₂	0	0
t_1, t_2, \dots	t_2	0 ₇	0	0	<i>t</i> ₃₀	04	0	1
test case inputs	t_2	0 ₂₀	0	1	<i>t</i> ₃₀	09	1	1
O_1, O_2, \dots	t_3	<i>o</i> ₂	0	0	t ₃₀	0 ₁₆	0	0
VESA .	t_3	03	0	0	<i>t</i> ₃₁	<i>o</i> ₂	1	0
the VESA-model	t_3	08	0	0	<i>t</i> ₃₁	04	0	1
of expert #2	t_3	0 ₂₀	1	0	<i>t</i> ₃₁	08	0	1
	t_4	<i>o</i> ₂₃	0	0	<i>t</i> ₃₁	<i>o</i> ₁₆	0	0



How to find human experts who are able and willing to cooperate for free ?

By choosing an "application" with a certain "entertainment factor":

Selection of an appropriate wine for a given dinner

6.1 The Knowledge Base

<u>Input space</u>: $I := [s_1, s_2, s_3]$:

- $s_1 \in \{ pork, beef, veal, fowl, ..., fish, ..., goat cheese, ..., fruit dessert, ice cream \}$
- $s_2 \in \{ \text{ non}(raw), \text{ steamed, boiled, grillesd, fried, } ... \}$
- $s_3 \in \{Asian, Western\}$

<u>Output space</u>: $O := \{ o_1, o_2, ..., o_{24} \}$ with

- $o_I = Red$ wine, fruity, low tannin, less compound
- $o_2 = Red$ wine, young, rich of tannin
- •

<u>Rule base</u>: $R := \{r_1, r_2, ..., r_{45}\}$ with

- $r_1 : o_1 \leftarrow (s_1 = fowl)$
- $r_2: o_1 \leftarrow (s_1 = veal)$

•
$$r_3: o_2 \leftarrow (s_1 = pork) \land (s_2 = grilled)$$

6.2 The Test Cases

... have been generated with a technology as introduced in former papers.

The resulting "Reasonable Set of Test Cases" (*ReST*) is:

t_1	pork	boiled	Asian	<i>t</i> ₂₂	fish	steamed	Western	
<i>t</i> ₂	pork	grilled	any	t ₂₃	fish boiled		Asian	
<i>t</i> ₃	pork	fried	any	t ₂₄	fish	grilled	any	
<i>t</i> ₄	pork	stewed	any	t ₂₅	fish	fried	any	
<i>t</i> ₅	beef	boiled	Asian	t ₂₆	fish	stewed	Asian	
<i>t</i> ₆	beef	grilled	any	t ₂₇	fish	deep fried	Asian	
<i>t</i> ₇	beef	fried	any	<i>t</i> ₂₈	hard cheese	non	Western	
<i>t</i> ₈	beef	stewed	any	t ₂₉	hard cheese	casserole	Western	
<i>t</i> ₉	veal	boiled	any	<i>t</i> ₃₀	hard cheese	deep fried	Western	
<i>t</i> ₁₀	veal	grilled	any	<i>t</i> ₃₁	soft cheese	non	Western	
<i>t</i> ₁₁	veal	fried	any	<i>t</i> ₃₂	soft cheese	casserole	Western	
<i>t</i> ₁₂	veal	stewed	any	<i>t</i> ₃₃	soft cheese	deep fried	Western	
<i>t</i> ₁₃	venison	boiled	any	<i>t</i> ₃₄	goat cheese	non	Western	
<i>t</i> ₁₄	venison	grilled	any	<i>t</i> ₃₅	goat cheese	casserole	Western	
<i>t</i> ₁₅	venison	fried	any	<i>t</i> ₃₆	goat cheese	deep fried	Western	
<i>t</i> ₁₆	venison	stewed	any	<i>t</i> ₃₇	blue mold cheese	non	Western	
<i>t</i> ₁₇	fowl	boiled	any	<i>t</i> ₃₈	blue mold cheese	casserole	Western	
<i>t</i> ₁₈	fowl	grilled	any	t ₃₉	blue mold cheese	deep fried	Western	
<i>t</i> ₁₉	fowl	fried	any	t ₄₀	fruit dessert	non	any	
<i>t</i> ₂₀	fowl	stewed	any	t ₄₁	aromatic dessert	non	any	
<i>t</i> ₂₁	fish	non	Asian	t ₄₂	ice cream	non	any	

6.3 Application Conditions

The experimentation took place with

- \succ three human experts e_1 , e_2 , e_3
- > a test case set **ReST** = { t_1 , t_2 , ..., t_{42} }
- session schedule:

session	experts			VESAs			examined test case inputs	
number	<i>e</i> ₁	<i>e</i> ₂	<i>e</i> ₃	VESA ₁	VESA ₂	VESA ₃	out of $\Pi_I(ReST)$	
1	+	+	+	-	-	-	$\Pi_{I}(ReST^{I}) := \{ t_{1},, t_{28} \}$	
2	\oplus	+	+	+	-	-	$\Pi_{I}(ReST^{2}) := \{ t_{15},, t_{42} \}$	
3	+	\oplus	+	-	+	-	$\Pi_{I}(ReST^{3}) := \{ t_{1},, t_{14}, t_{29},, t_{42} \}$	
4	+	+	\oplus	-	-	+	$\Pi_{I}(\operatorname{ReST}^{4}) := \{ t_{i} : t_{i} \bmod 3 \neq 0 \}$	

takes part in the session - does not take part in the session

 \oplus takes part in the session only for being compared with its VESA

Notational Conventions

VKBⁱ denotes the VKB as developed after the *i* -th session

+

- VESAⁱ denotes the behavior of the VESA which models the behavior of expert e_k after the *i* -th session
- **ReST**^{*i*} denotes the test case set used in the *i* -th session
- EKⁱ denotes the available "external knowledge" of the VKB in the *i* -th session: EKⁱ := Π₁(VKBⁱ) ∩ ReSTⁱ

6.4 Desired Outcome of the Experiment

The experiment should provide answers to the following questions

- 1. Does the VKB contribute to the validation sessions at an increasing rate with an increasing number of validation sessions?
 - How many external solutions (outside the expertise of the current expert panel) are introduced into the rating process by the VKB?
- 2. Does the VKB contribute valid knowledge (best rated solutions) in an increasing rate with an increasing number of validation sessions?
 - How many of the introduced solutions win the rating contest against the solutions of the current expert panel?
- 3. Does the VKB increasingly gain the human expertise as number of validation sessions increases?
 - How many new best rated solutions are introduced into the VKB after a validation session?
- 4. Do the VESAs models of their human source improve with in increasing number of validation sessions?
 - Do the VESAs provide the same solutions and ratings as their human counterpart?

To quantify these measures, we computed after each session (session # i)

- the number a_i of cases from VKB ⁱ⁻¹, which were the subject of the rating session and relate it to | EKⁱ |:
 A_i := a_i / | EKⁱ |
- the number \mathbf{b}_i of cases from VKB ⁱ⁻¹, which provided the optimal (best rated) solution and relate it to | EKⁱ | : $\mathbf{B}_i := \mathbf{b}_i / | EK^i |$
- the number c_i of cases from VKB ⁱ⁻¹, for which a new solution has been introduced into VKB and relate it to | EKⁱ | : $C_i := c_i / | EK^i |$
- the number d_i of solutions and ratings, which are identical responses of e_{i-1} and VESA $_{i-1}$ and relate it to the number of required solutions and ratings: $D_i := d_i / \#$ responses

Thus, desired answers can be formalized

- 1. Does the VKB contribute to the validation sessions at an increasing rate with an increasing number of validation sessions: $A_4 > A_3 > A_2$?
- 2. Does the VKB contribute valid knowledge (best rated solutions) in an increasing rate with an increasing number of validation sessions: $B_4 > B_3 > B_2$?
- 3. Does the VKB increasingly gain the human expertise as number of validation sessions increases: $C_2 > C_3 > C_4$?
- 4. Do the VESAs model of their human source improve with in increasing number of validation sessions: $D_4 > D_3 > D_2$?

7 Test Results

Toes the VKB contribute to the validation sessions at an increasing rate with an increasing number of validation sessions: $A_4 > A_3 > A_2$?

- # of new external solutions from VKB:
 - 1 (of 14 possible in EK) in session 2
 - 2 (of 28) in session 3
 - 24 (!) (of 28) in session 4
 0.85 >> 0.071 ≥ 0.071
- Obviously, the VKB needs to gain some "initial experience" before it contributes a remarkable number of new solutions.
- *The desired effect became remarkable in the 4th session.*
- 2. Does the VKB contribute valid knowledge (best rated solutions) in an increasing rate with an increasing number of validation sessions: $B_4 > B_3 > B_2$?
 - # of new external solutions, which won the rating session:
 - 0 (out of 14) in session 2
 - 0 (out of 28) in session 3
 - 2 (out of 28) in session 4:

- $0.071 \geq 0 \geq 0$
- *However, it is remarkable that 2 solutions which were not provided by the panel got very best marks by the same panel.*
- This is what we want the VKB to do: Contributing better knowledge than the current human experts. The "collective experience" of former panels reveals to be better than the current panel.

- 3. Does the VKB increasingly gain the human expertise as number of validation sessions increases: $C_2 > C_3 > C_4$?
 - # of cases introduced into VKB:
 - 7 (of 14) after session 2
 - 16 (of 28) after session 3
 - 17 (of 28) after session 4:

$$0.5 \le 0.57 \le 0.61$$

- *Here, our expectation was not met!*
- The reason is probably, that the domain knowledge itself as well as its reflection in human minds changed from session to session.
- Most interesting problem domains are not static by nature; individual peoples' opinions are not static by nature.
- 4. Do the **VESA**s model of their human source improve with in increasing number of validation sessions: $D_4 > D_3 > D_2$?
 - # of identical responses by the expert and his/her VESA
 - 27 (of 63) in session 2
 - 78 (of 126) in session 3
 - 90 (of 150) in session 4: $0.6 \approx 0.62 > 0.43$
 - Again, we explain this as the result of changing minds by the experts.
 - A crucial problem is
 - the interpretation of a verbal case description and
 - some latent dependence from other circumstances than the case input itself (the mood, e.g.).

Lessons Learnt

Derived improvements to the "collective experience" in VKB

- ✓ Outdating knowledge
 - Should some knowledge, which receives "bad marks" by several expert panels over many sessions removed from VKB?
- Completion of VKB towards other than former test cases
 - *VKB so far can only provide its "experience" only for historic cases.*
 - How to derive experience from VKB for other cases? Is a CBR concept appropriate for this problem?
 - Current work: Adapting the k-NN Data Mining Approach towards solving this problem

Derived improvements to the "individual experience" in VESAs

- ✓ Non-deterministic problem domains
 - A certain solution might be "correct" in the eyes of an expert, even if it is not the one he would provide as a solution to the presented case.
 - In many interesting problem domains cases have several acceptable solutions.
 - > This drawback has already been fixed:
 - VESA's solving behavior is modeled based only on the solving behavior of its human counterpart.
 - VESA's rating behavior is modeled based only on the rating behavior of its human counterpart.
- Determination of a "most similar expert"
 - The prototype experiment revealed, that there are often several experts' solution in the VKB with the same degree of similarity.
 - In this case we suggest to consider another parameter: We should look for an expert with the <u>most recent</u> identical (solving or rating) behavior.
 - This is reasonable, because also such similarities are subject to natural change over time.

Derived improvements to the "individual experience" in VESAs (cont'd)

- ✓ Permanent validation of the VESAs
 - The concept will be refined by adding some permanent ,, selfvalidation " of each VESA by
 - submitting VESA's solution to the rating process of its human counterpart and
 - comparing VESA's rating with the rating of its human counterpart.

Thus, some statement about each VESA's quality can be derived:
 The number of VESA's solutions, which are rated by its human counterpart as ,, correct" and
 the number of VESA's ratings which are identical with those of its human counterpart

are measures about the performance of the human behavior model.

✓ Completion of VESAs towards other than former test cases

In case there is no ,, most similar expert "who ever considered (solved or rated) a current case, a concept of determining a ,, most likely response "of the modeled expert needs to be developed.

8 Summary and Conclusion

- 1. Ensuring validity of AI systems requests methods beyond conventional software engineering techniques. The only source of domain knowledge is often human expertise.
- 2. Human expertise is often uncertain, undependable, contradictory, unstable, it changes over time and is quite expensive.
- 3. The concept of *VKB* is the key to use this resource more efficiently towards valid systems. The VKB approach includes all aspects of "collective historical experience" that have been provided by previous expert panels.
- 4. While *VKB* aims at modeling the human experts' collective and most accepted (best rated) knowledge, the *VESA* concept aims at modeling the individual human experts.
- 5. Experiments revealed that the *VKB* and *VESA* approach needs to be refined with respect to
 - their completion towards other than (previous) test cases

Ger Under construction: Adapting the k-NN data mining approach

and VESA needed to be developed further with respect to

- ✓ the nature of the non-deterministic problem domains (done!)
 - Solving cases based on a previous rating is not appropriate
- their permanent validation