선박의 종류별 선원의 행동오류 추정과 예측에 관한 기초 연구

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요 약 : 선원의 행동오류는 해양사고를 야기하는 하나의 직접적인 원인이기 때문에 이를 이해하는 것은 해양사고 예방에 근본이 된다. 선원의 행동오류를 이해하기 위해서는 행동오류를 추정하고 예측할 수 있어야 한다. 본 연구에서는 은닉 마르코브 모델(Hidden Markov Model, HMM)을 이용하여 선원들의 행동오류를 추정하고 예측하였다. 아울러 5가지 선박의 종류 각각에 나타나는 선원들의 행동오류를 서로 비교 분석하였다. 모델에 사용한 데이터는 해양안전심판원의 해양사고 보고서에 기록된 내용을 SRKBB(Skill-, Rule- and Knowledge-Based Behavior) 모델을 기반으로 분류하고 관측 수열을 생성하며 라벨링 작업을 통해서 구축하였다. 구축한 데이터를 적용하여 HMM을 보정하고 파라미터를 획득하여 선원들의 행동오류에 관한 모델을 구축하였다. 실험 결과, 선박 종류별로 선원들의 행동오류의 패턴은 서로 다르고, 이를 통해서 선박종류별 해기사들의 행동오류의 추정과 예측이 가능함을 일차적으로 확인할 수 있었다. 추후 본 연구를 지속 전개하여 해양사고 예방을 위한 인적오류의 저감에 기여할 수 있는 방안을 모색할 예정이다.

핵심용어 : 해양사고, 인적오류, 행동오류, 은닉 마르코브 모델, SRK 모델

◆ **Summary of SRKBB related models and concepts for Stage 1 (Situations)**

Stage	Level	Definition	Example Mariner's behaviors
St. 1 Situation	L1 Routine	• In the skill-based domain, including automated, more or less subconscious routines, performance is controlled by stored patterns of behavior in a time-space domain (Rasmussen, 1982). • Skill-based behavior occurs when workers are extremely expert at their jobs, so they can do the everyday, routine tasks with little or no thought or conscious attention (Norman, 2013).	A physical routine behavior that manipulates the lever of a Telegraph
	L2 Familiar	• The rule-based domain includes performance in familiar situations controlled by stored rules for coordination of subroutines, and errors are typically related to mechanisms like wrong classification or recognition of situations, erroneous associations to tasks, or to memory slips in recall of procedures (Rasmussen, 1982). • This level is applicable to tackling familiar problems in which solutions are governed by stored rules (productions) of the type if (state) then (diagnosis) or if (state) then (remedial action) (Reason, 1990)	Behavior when a situation is given and rules or procedures are applied
	L3 Unfamiliar	• During unfamiliar situations, faced with an environment for which no know-how or rules for control are available from previous encounters, the control of performance must move to a higher conceptual level, in which performance is goal-controlled and knowledge-based (Rasmussen, 1982). • Behaviors are necessary when skills- or rules- are either unavailable or inadequate such that problem solving and planning are called for in order to meet the demands of the unfamiliar situation (Honless et al., 2006).	Behavior when you need to rely on knowledge of navigation for unfamiliar situation

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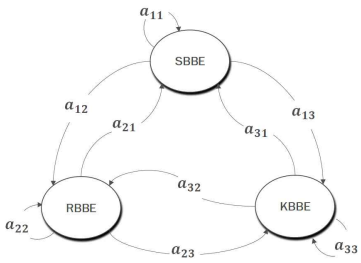
◆ 3-state ergodic HMM

State transition probability from state i to state j: $A = \{a_{ij}\}$, $a_{ij} = P(q_j \mid q_i), i, j = 1, \cdots N$



◆ **Results of model for each accidents**

- **MAPE 3.6 ~ 13.9**

Accident type	Model	MAPE
Collision	HMM1	9.95
Contact	HMM2	9.17
Grounding	HMM3	11.12
Capsizing	HMM4	13.98
Fire and/or Explosion	HMM5	4.22
Sinking	HMM6	12.10
Machinery failure	HMM7	3.65

◆ **Parameter estimation result**

Model	Terms of transmission, aij			
		j=1	j=2	j=3
HMM 1	i=1	0.5889	0.2077	0.2033
	i=2	0.3449	0.4614	0.1936
	a(i=3)	0.4723	0.2352	0.2925
HMM 2	a(i=1)	0.3621	0.3621	0.2759
	a(i=2)	0.4035	0.4035	0.193
	a(i=3)	0.3846	0.3333	0.2821
HMM 3	a(i=1)	0.4724	0.2835	0.2441
	a(i=2)	0.5441	0.2353	0.2206
	a(i=3)	0.4348	0.2319	0.3333
HMM 4	a(i=1)	0.3793	0.4138	0.2069
	a(i=2)	0.2821	0.4103	0.3077
	a(i=3)	0.28	0.44	0.28
HMM 5	a(i=1)	0.7786	0.1	0.1214
	a(i=2)	0.875	0.0625	0.0625
	a(i=3)	0.8421	0.0526	0.1053
HMM 6	a(i=1)	0.4902	0.2941	0.2157
	a(i=2)	0.4474	0.3684	0.1842
	a(i=3)	0.3333	0.2963	0.3704
HMM 7	a(i=1)	0.7463	0.1343	0.1194
	a(i=2)	0.7273	0.0909	0.1818
	a(i=3)	0.9	0.1	0

◆ **최확 경로 계산 결과**

- **최확 경로 계산 결과 : 일부 유사한 경로도 있고, 매우 다른 경로도 도출됨 -> HMM 식별력 있음을 의미**
- **다음 슬라이드에서 확인**

Model	Item	Most probable likelihood path and log probability									
HMM 1	Symbol	4	14	23	13	5	1	24	2	15	10
	Comb	(1,2,3)	(0,1,3)	(2,1,0)							
	Log(p)	-1.53	-1.66	-2.1	-2.29	-2.49	-2.75	-3.16	-3.17	-3.32	-3.65
HMM 2	Symbol	14	4	1	17	13	23	24	5	27	2
	Log(p)	-1.6	-2.39	-2.53	-2.62	-2.67	-2.75	-2.75	-2.79	-2.87	-3.01
HMM 3	Symbol	14	4	1	5	24	10	13	2	15	11
	Log(p)	-1.66	-2.1	-2.16	-2.34	-2.6	-3.23	-3.23	-3.29	-3.3	-3.32
HMM 4	Symbol	14	15	4	18	27	5	17	1	10	23
	Log(p)	-1.34	-2.15	-2.39	-2.66	-2.72	-2.73	-2.89	-2.95	-3.12	-3.19
HMM 5	Symbol	1	4	5	27	24	15	14	23	13	2
	Log(p)	-0.75	-1.94	-2.55	-3.16	-3.31	-3.32	-3.34	-3.49	-3.72	-3.81
HMM 6	Symbol	5	14	4	15	24	18	13	27	1	10
	Log(p)	-1.94	-2	-2.08	-2.32	-2.56	-2.67	-2.82	-2.92	-3.04	-3.21
HMM 7	Symbol	4	1	5	14	15	18	11	23	26	13
	Log(p)	-1.11	-1.74	-1.81	-2.51	-3.02	-3.33	-3.71	-3.73	-3.73	-3.77

◆ **Comparison of model**

	HMM 1	HMM 2	HMM 3	HMM 4	HMM 5	HMM 6	HMM 7
HMM 1	-5427.22	-5888.84	-6080.61	-6657.07	-7476.95	-6135.46	-7268.9
HMM 2	-444.381	-408.304	-436.85	-474.816	-532.043	-442.588	-546.813
HMM 3	-771.17	-752.181	-704.099	-859.429	-954.025	-798.049	-919.657
HMM 4	-273.422	-248.946	-268.698	-232.863	-334.268	-249.049	-340.37
HMM 5	-485.676	-462.516	-449.423	-527.999	-333.449	-498.744	-415.474
HMM 6	-339.824	-324.388	-336.792	-332.316	-405.81	-304.226	-416.194
HMM 7	-220.145	-230.41	-214.625	-249.291	-220.708	-222.367	-181.323

◆ **모델 사이의 식별력, 모델 사이의 상관관계 계산 결과**

Model	Items	Coefficients and p-Values						
			HMM1	HMM2	HMM3			
HMM1	Coefficient	1	0.900106	0.889849	0.696214	-0.6603	0.798339	-0.32396
	p-Value	0	0.005737	0.007283	0.082276	0.106467	0.031362	0.478434
HMM2	Coefficient		1	0.915902	0.837281	-0.62842	0.909529	-0.52377
	p-Value		0	0.003763	0.018754	0.130671	0.004501	0.227586
HMM3	Coefficient			1	0.67876	-0.55853	0.776686	-0.24482
	p-Value			0	0.093623	0.192504	0.039968	0.596723
HMM4	Coefficient				1	-0.86625	0.949286	-0.77037
	p-Value				0.001<	0.011678	0.001082	0.042695
HMM5	Coefficient					1	-0.80346	0.484351
	p-Value					0.001<	0.029494	0.270693
HMM6	Coefficient						1	-0.6429
	p-Value						0	0.119357
HMM7	Coefficient							1
	p-Value							0.001<

Linear or rank correlation
a matrix of p-values for testing the hypothesis of no correlation against the alternative that there is a nonzero correlation. Each element of PVAL is the p-value for the corresponding element of RHO. If PVAL(i, j) is small, say less than 0.05, then the correlation RHO(i, j) is significantly different from zero.
'Pearson' (the default) computes Pearson's linear correlation coefficient

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References

[1] Chauvin C., Clostermann, J.P. and Jean-Michel Hoc(2008), "Situation Awareness and the Decision-Making Process in a Dynamic situation: Avoiding collisions at sea", Journal of cognitive engineering and decision making, Vol 2, pp. 1-23.

[2] Drivalou, S. and Marmaras, N.(2009). "Supporting skill-, rule-, and knowledge-based behaviour through an ecological interface: An industry-scale application", International Journal of Industrial Ergonomics, Vol. 39(6), pp. 947-965.

[3] Imbert, J. P., Granger, G., Benhacene, R., Golfetti, A., Bonelli, S., and Pozzi, S.(2015), "Skill, Rule and Knowledge-based Behaviors Detection during Realistic ATM Simulations by Means of ATCOs' Brain Activity", SESARWPE.

[4] KMST(2017), Written Verdict. [Online], Retrieved from https://data.kmst.go.kr/kmst/verdict/writtenverdict/selectwrittenverdict.do.

[5] Lin, C. J., Shiang, W. J., Chuang, C. Y. and Liou, J. L.(2014), "Applying the Skill-Rule-Knowledge Framework to Understanding Operator's Behaviors and Workload in Advanced Main Control Rooms", Nuclear Engineering and Design, Vol. 270, pp. 176-184.

[6] Park, D. J., Cho, C. Y. and Yim, J. B. (2017), "A Research on the method of mariner's SRK Behaviors", Joint Conference 2017, KOSOMES, Mokpo, Korea, April 27-28, p. 59.

[7] Park, D. J.(2018), “A study on acquisition of SRK behavior distribution function for reducing marine accidnets caused by human error", Master thesis, Mokpo National Maritime University.

[8] Rasmussen, J.(1983), "Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models", IEEE transactions on systems, man, and cybernetics, Vol. 3, pp. 257-266.

[9] Rasmussen, J.(1982), "Human errors. A taxonomy for describing human malfunction in industrial installations", Journal of occupational accidents, Vol. 4(2-4), pp. 311-333.

[10] Reason, J.(1990), "Human Error", Cambridge University, New York, USA.

[11] Yim, J.B ., Yang, W. J. and Kim, H. T.(2014), "Marine Accident Analysis", Je-Il-Gi-Hwik, pp. 1-392.

[12] Yim, J. B.(2017a), "A Study on the Analysis and Identification of Seafarers' Skill-Rule-Knowledge Inherent in Maritime Accidents", KOSMES, Vol. *23*(3), pp. 224-230.

[13] Yim, J. B.(2017b), "A Study on the Reduction of Common Words to Classify causes of Marine Accidents", Korean Institute of Navigation and Port Research, Vol. 41(3), pp. 109-117.

[14] L. Rabiner and B. Juang(1986), "An introduction to hidden Markov models", 3 ASSP Magazine, IEEE [see also IEEE Signal Processing Magazine] 4-16.

[15] M. Hiroshi (1997), “Supervised learning of hidden Markov models for sequence discrimination,” Proceedings of the first annual international conference on Computational molecular biology, Santa Fe, New Mexico, United States.

[16] L. W. Baum and T. Petrie (1966), "Statistical Inference for Probabilistic Functions of Finite State Markov Chains," The Annals of Mathematical Statistics, pp. 1554-1563.