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Applying Hidden Markov Models to visual activity analysis for simple digital control panel operations

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Abstract. The paper presents an application of Hidden Markov Models (HMM) to fixations' sequences analysis. The examination concerns eye tracking data gathered during performing simple comparison and decision tasks for four versions of plain control panels. The panels displayed the target and current velocity either on a digital or analog (clock-face) speedometers. Subjects were to decide whether increase or decrease the current speed by pressing the appropriate button. The obtained results suggest that females, generally exhibit different covert attention patterns than men. Moreover, the article demonstrates the estimated four HMM with three hidden states for every examined control panels variant and provides discussion of the outcomes.

Keywords: ergonomics · control panel design · human visual behavior · human-computer interaction

1 Introduction

The human visual activity may be analyzed by the eye tracking investigations. The visual scanpath typically registered by such systems consists of a sequence of fixations and saccades. Generally, remaining for a longer time within a specific, constraint area is considered to be a fixation while rapid, ballistic changes in eye position are called saccades. It is widely believed, and assumed that the visual processing takes place when fixating whereas during saccadic jumps the information extraction is suppressed. By examining a series of fixations and saccades one can infer about the attention shifting process that accompanies visual task executions.

Ellis and Stark (1986) suggested that scanpaths can be modeled by a stochastic first-order Markov process, where the fixation position depends on the location of the previous fixation. In recent years more and more popular becomes the extension of this approach to Hidden Markov Models. The interest in this type of analysis is directly related to latest findings from visual processing psychology that differentiated between the overt and covert attention (Findlay and Gilchrist, 2003). Observable eye movements are obviously associated with overt attention while hidden states from HMM are coupled with shifting covert attention. HMM tools allow for finding stochastic relations between observations and hidden states and, thus, are very useful in broadening the basic knowledge about attentional visual processes.

Liechty et al. (2003), for instance, showed in their study, that registered during visual analysis of printed advertisements saccades' lengths may be explained by means of the two-states HMM. These states, according to authors reflect two states of covert attention – local and global. In the work of Hayashi (2003), in turn, it was demonstrated that the HMM states estimated from pilots' fixations can be associated with tasks performed during plane landing. The number of hidden states obtained from HMM indicates that pilots organize the covert attention changing process differently, depending on their experience. A similar approach applied by Chuk et al. (2014) to the analysis of the face recognition task yielded various visual activity strategies among individuals. The authors identified two specific attention patterns – holistic and analytic. Experiments conducted by Simola et al. (2008) revealed that it is possible to discover particular, common patterns of attention used during textual information search. In this case, the HMM scanpaths investigation provided evidence for existing three consecutive hidden states defined as scanning, reading and the answer.

The problem of identification of various tasks performed by humans based on their visual activity registered in a scanpath form is subject to investigation of many researchers. The importance of this issue results, among other things, from its possible practical application in the domain of intelligent interactive systems. In such a perspective the HMM may play a significant role. For example, Haji – Abolhassani and Clark (2014) studied visual observations tasks of black and white pictures and showed using HMM and clustering methods that it is possible to detect the visual task type given the specific eye ball movements data. Furthermore, Courtemanche et al. (2011) proposed a framework allowing for identification of tasks having hierarchical structures in human-computer interaction processes. This was modeled by a Layered version of HMM.

The present study is focused on the visual activity observed during performing easy human-machine interaction tasks. The analyses, carried out in the HMM perspective aim at attempting to answer fundamental questions inspired by the abovementioned research. First, what types of the visual strategies and attention shifts patterns are employed by subjects while operating control panels and how do they depend on the interface design? Secondly, what are the qualitative differences (if any) between subjects' visual activities? The latter issue was examined between males and females.

The remainder of the article is organized as follows. At first, the idea of the HMM is shortly described, then the control panel experiment is overviewed. Next, HMM simulation results are demonstrated and discussed.

2 Hidden Markov Models overview

An HMM is usually specified by the following components (see e.g. Rabiner, 1989): **(1)** a set of N states in a model: $\boldsymbol{S} = \{s_1, s_2, ..., s_N\}$, **(2)** a group of M observation symbols for each state called also the vocabulary or alphabet: $\boldsymbol{V} = \{v_1, v_2, ..., v_M\}$, **(3)** a states' transition probability matrix which specifies the probability of moving from state i to state j: $\boldsymbol{A} = \{a_{ij}\}$, where $a_{ij} = P[q_{t+1} = S_j \mid q_t = S_i]$; $1 \le i, j \le N$; q_t is the state at time t, **(4)** The observation symbol likelihoods distribution in state j, also called emission probabilities matrix: $\boldsymbol{B} = \{b_j(k)\}$, where $b_j(k) = P[v_k \text{ at t } | \ q_t = S_j]$; $1 \leq j \leq N$, $1 \leq k \leq M$, **(5)** the Markov chain starting probability distribution $\boldsymbol{\pi} = \{\pi_i\}$, where $\pi_i = P[q_1 = S_i]$, $1 \leq i \leq N$. In short, the full HMM model requires the specification of states, symbols, and three sets of probabilities distributions: $\lambda = (A, B, \pi)$. Such a model can generate the sequence of observations: $O = O_1O_2 \cdots O_T$, where every O_t is one of the V symbols, and T is the observation sequence length. In the present study, a set of (A, B, π) are being sought given the observation sequences O, assumed number of states N and a defined vocabulary V.

3 Control panels experiment overview

The current paper Hidden Markov modeling is based on the eye tracking results from an experimental study presented by Michalski (2016). Therefore, only a very brief overview of this investigation is provided in this section.

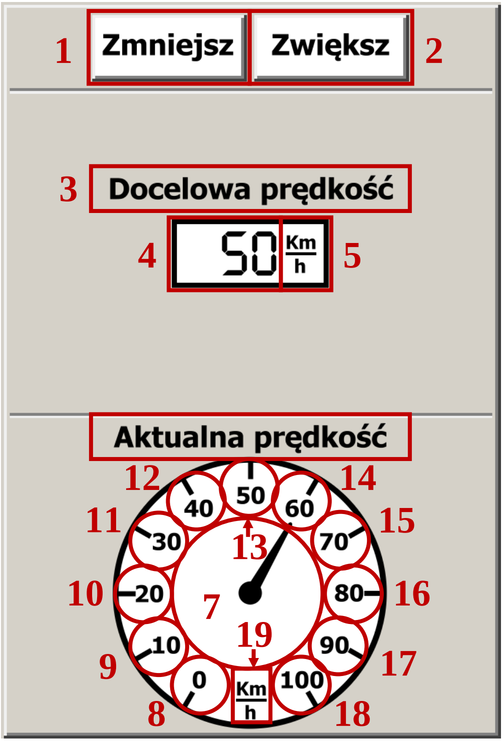
The visual activity data came from 33, young subjects (15 women, and 18 men) and were registered by a SMI RED500 stationary eye tracker. The participants performed simple comparison and decision making tasks regarding the digital control panels displayed by JavaScript in a web browser. Specifically, they were to compare target and current velocities, decide whether to increase or decrease the current value to get the desired one, and click with a mouse on the proper button.

The designed stimuli differed in the speedometer types. Digital and analog (clock-face) speedometer versions and types of displayed information produced four experimental conditions: **(1) AA** – target and current velocities presented on analog speedometers, **(2) AD** – the target demonstrated on an analog while the current on a digital version, **(3) DA** – the target on digital and the current on analog, and finally both velocities presented on digital speedometers **(4) DD**. Fig. 1 shows one (DA) of the four control panel types examined in this study, with superimposed areas of interests used for the present study modeling purposes. Subjects performed six trials per each speedometer type combination factor (STC), they resulted from combining three target velocity values (20, 50, 80 Km/h), and the required response type (Increase, or Decrease). Each subject tested all types of control panels presented randomly.

4 Modeling visual activity by Hidden Markov Models

4.1 Preparation of eye tracking data for HMM

The idea of preparing the data for HMM was similar to the one used in a work of Hayashi (2003). However, instead of using the whole instruments as the HMM symbols, the present study employs much smaller panel components for this purpose. The identified areas of interests for one of the examined panel versions (DA) are graphically illustrated in Fig. 1. The AOIs and their abbreviations presented next to the panel were analogically created for the remaining three speedometer type combinations The sequences of fixations observed on these salient panel components towards which subjects direct their attention were used to train the HMM. The data were exported by a SMI BeGaze software Ver. 3.6, and processed in the STATISTICA ver. 12.



1. **D** (Decrease)
2. **I** (Increase)

3. **TD-Txt** (Target Digital)
4. **TD-V** (Velocity Value)
5. **TD-Kmh**

6. **CA_Txt** (Current Analog)
7. **CA_Cen** (Center)

8. **CA-V0**
9. **CA-V10**
10. **CA-V20**
11. **CA-V30**
12. **CA-V40**
13. **CA-V50**
14. **CA-V60**
15. **CA-V70**
16. **CA-V80**
17. **CA-V90**
18. **CA-V100**

19. **CA_Kmh**

Fig. 1. Areas of interests defined for one of the digital control panel variants. The AOIs and their abbreviations presented next to the panel were analogically created for the remaining three speedometer type combinations.

4.2 HMM estimation

The initial, transition, and emission probabilities for first order, discrete time, hidden Markov models were estimated using the Baum-Welch algorithm (Baum, 1972) implemented by Murphy (1998, 2005). The maximum number of iterations in this algorithm was set at 1000 and the convergence threshold was specified at 0.0001. All the estimations and calculations were performed in a MatLab (7.11.0) R2010b package.

4.3 Gender and speedometer effects in HMM

A simulation experiment was performed to verify how many hidden states will best model the four versions of analyzed control panels. Since the findings regarding a number of subjects' visual behavior characteristics while performing the experimental task presented by Michalski (2016) suggest that females probably apply qualitatively different visual strategies than males, the models were examined separately for men and women. Overall 32 conditions were investigated involving four possible hidden states (from 3 to 6), four control panel types (AA, AD, DA, DD), and the gender factor: 4 (States) × 4 (STC) × 2 (Gender).

As the estimated HMM parameters may depend on their starting values, each time for every estimated model 100 simulations were performed with randomly chosen initial states, transitions', and emissions' probabilities. The models were assessed by means of the Akaike's (1973) Information Criterion (AIC), and Schwarz's (1978) Bayesian Information Criterion (BIC). The obtained mean (standard deviations in brackets) and minimum values for AIC, BIC along with log-likelihoods are put together in Table 1. The smaller values of AIC and BIC signify more accurate models.

The evaluation of obtained models in these simulations according the AIC and BIC criteria is ambiguous. The AIC values suggest that the gender factor significantly differentiates the attentional process dynamics recorded during executing experimental tasks. The data show that generally the smaller number of hidden states is characteristics of females than males. Almost for all examined control panel interfaces, the more accurate models required one state less for females than males. Given the tiny differences between the two smallest AIC values in two cases that is, AA and DD for females and models with a smaller number of hidden states were chosen due to the parsimony principle.

Hayashi (2003) analyzing the pilots eye movement data during landing found that their visual behavior described by the optimal number of hidden states depended on their flying experience. Models with a bigger number of hidden states better fit to the experimental data for more experienced pilots. The author explains the fact by a more detailed analysis of instruments which leads to a more detailed structure of the mental attention model. Although in our experimental tasks the experience is not directly connected with gender, but it seems that designed control panel operations may be associated with car driving or computer simulation games – and these are rather closer to men. The above finding may provide a possible explanation of the somewhat unexpected result described in Michalski (2016). The analysis of effectiveness showed there that women committed more than twice as many mistakes (7.8%) while performing trials than men (3.7%, $\chi^2 = 6.1$, p = 0.013) which is in contrast with many research (e.g. Blatter et al., 2006). In light of the present study findings, this phenomenon could probably result from different covert attention distribution for females and males and worse mental representation of the studied problem in women. The suggested problems with correctly mapping the experimental task to females' internal mental representations were additionally visible in markedly longer fixations (Michalski, 2016) associated with more difficult tasks.

Analyzing simulation experiment results, one can also notice that the optimum number of hidden states (according to AIC) across the investigated control panel types is quite similar and amounts to 5 for men and 4 for females. Only for the Analog – Digital option models with a bigger number of states (6 states for males and 5 for women) are more accurate. This, in turn, sheds some more light on another surprising result from the analysis provided in Michalski (2016) regarding the statistically significantly worst mean operation times for the AD versus DA.

No.	STC	Gender	No of states	AIC		BIC		Log-likelihood	
				Mean	Min	Mean	Min	Mean	Min
1.	AA	Male	3	4320 (33)	4265	4784 (33)	**4728**	-2061 (16)	-2106
2.	AA	Male	4	4314 (33)	4261	4950 (33)	4897	-2021 (17)	-2056
3.	AA	Male	**5**	4318 (34)	**4256**	5137 (34)	5075	-1984 (17)	-2033
4.	AA	Male	6	4326 (31)	4271	5337 (31)	5282	-1947 (16)	-1989
5.	AA	Female	3	3906 (44)	3862	4360 (44)	**4316**	-1854 (22)	-1911
6.	AA	Female	**4**	3831 (52)	**3785**	4455 (52)	4409	-1780 (26)	-1870
7.	AA	Female	5	3843 (44)	**3785**	4646 (44)	4588	-1747 (22)	-1815
8.	AA	Female	6	3859 (34)	3808	4850 (34)	4798	-1714 (17)	-1772
9.	AD	Male	3	3802 (21)	3777	4127 (21)	**4102**	-1832 (10)	-1870
10.	AD	Male	4	3781 (22)	3756	4234 (22)	4209	-1795 (11)	-1841
11.	AD	Male	5	3766 (27)	3735	4355 (27)	4324	-1758 (14)	-1803
12.	AD	Male	**6**	3768 (24)	**3725**	4504 (24)	4460	-1728 (12)	-1763
13.	AD	Female	3	3122 (25)	3090	3436 (25)	**3403**	-1492 (13)	-1546
14.	AD	Female	4	3077 (44)	3032	3513 (44)	3468	-1443 (22)	-1492
15.	AD	Female	**5**	3056 (33)	**3020**	3624 (33)	3587	-1403 (16)	-1452
16.	AD	Female	6	3064 (26)	3027	3773 (26)	3735	-1376 (13)	-1438
17.	DA	Male	3	2913 (33)	2889	3211 (33)	**3187**	-1391 (16)	-1436
18.	DA	Male	4	2883 (27)	2853	3298 (27)	3267	-1350 (14)	-1396
19.	DA	Male	**5**	2877 (29)	**2842**	3418 (29)	3383	-1318 (14)	-1364
20.	DA	Male	6	2889 (22)	2860	3565 (22)	3536	-1294 (11)	-1329
21.	DA	Female	3	2346 (35)	2333	2631 (35)	**2619**	-1107 (18)	-1209
22.	DA	Female	**4**	2312 (32)	**2280**	2709 (32)	2677	-1064 (16)	-1103
23.	DA	Female	5	2309 (25)	2287	2828 (25)	2805	-1035 (12)	-1101
24.	DA	Female	6	2332 (14)	2309	2980 (14)	2957	-1016 (7)	-1056
25.	DD	Male	3	1889 (22)	1859	2044 (22)	**2014**	-908 (11)	-928
26.	DD	Male	4	1868 (22)	1851	2093 (22)	2076	-882 (11)	-914
27.	DD	Male	**5**	1860 (19)	**1840**	2162 (19)	2142	-860 (9)	-886
28.	DD	Male	6	1868 (14)	1849	2256 (14)	2238	-844 (7)	-874
29.	DD	Female	3	1513 (34)	1483	1661 (34)	**1631**	-721 (17)	-743
30.	DD	Female	**4**	1478 (26)	**1464**	1691 (26)	1677	-687 (13)	-725
31.	DD	Female	5	1479 (15)	**1463**	1767 (15)	1750	-669 (8)	-719
32.	DD	Female	6	1493 (12)	1475	1863 (12)	1845	-656 (6)	-682

Table 1. The Hidden Markov Model simulation results. Standard deviations in brackets.

t could be predicted that having identical combination of speedometer types presenting the same type of physical value (velocity), the efficiency results would be comparable. However, as it can be observed from a different number of desired hidden states in demonstrated HMM, these versions of control panels are not equivalent. It seems that attentional patterns necessary to process target and current velocity values are considerably different. This discrepancy probably underlain the differences between AD vs. DA registered for task completion times, saccade counts, as well as scanpath lengths.

The AIC and BIC indicators penalize the log-likelihood in such a way that the model assessment takes the maximum likelihood principle when the number of model parameters to be estimated is as small as possible. In the BIC criterion the penalization effect is more severe than in AIC which can be seen in Table 1. According to this criterion the suggested best model for all examined conditions includes only three hidden states. The search for three states HMMs depending on the control panel design is an attempt to answer the second research question of this study.

4.4 Analysis of HM models for speedometer type combination

Analogically as in the examination described in the previous section a series of 100 HMM simulations were performed for all four speedometer type combinations assuming three hidden states. From the obtained group of models, the ones with the smallest log-likelihood value were chosen and presented in Table 2. The initial states probabilities are displayed in the second row, while the three further rows contain the transition probabilities distribution. The remaining rows include the emission matrix probabilities.

The HM models (A, B, π) estimated from the fixation sequences registered for all subjects examining the given control panel interface variant exhibit far-reaching stability in attention shifting strategy between these three states. The outcomes seem to be quite similar irrespective of the panel construction. The analysis of models' parameters allow for relating the obtained hidden states with the executed tasks. Examining, for example, the DA control panel from Fig. 1 and the HMM for this variant presented in Table 2(c) one can easily notice that the most probable starting state is S_2 ($p = 0.85$). The biggest emission probabilities associated with this state indicate that it is strongly related with fixating on the target velocity. Similar values of probabilities were estimated for the target caption and value (TD-Txt, TD-V): 0.42 and 0.45 respectively. Thus, the S_2 can be specified as the ***Target identification state***. The S_3 state generates the biggest emission probabilities for CA-Txt and CA-Cen symbols (0.27) that is, the areas presenting the current velocity caption and the analog speedometer indicator. As a result of this, the S_3 can be called ***Current state analysis*.** The last state S_1 with maximum probabilities values (0.30) for D and I (Decrease and Increase) buttons observations can be described as ***Decision and execution***. Comparable patterns of probabilities distributions for $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{\pi}$ are visible in all versions of investigated control panels, thus similar process of identifying state's meaning can also be replicated for the remaining variants.

(a). AA	S1	S2	S3
π	.03	.84	.13
S1	.91	.00	.37
S2	.09	.68	.00
S3	.00	.32	.63
TA-Txt	.13	.26	.00
TA-Cen	.12	.30	.03
TA-V0	.01	.01	.00
TA-V10	.01	.00	.03
TA-V20	.01	.03	.06
TA-V30	.01	.03	.01
TA-V40	.01	.05	.00
TA-V50	.05	.10	.01
TA-V60	.00	.00	.00
TA-V70	.02	.02	.01
TA-V80	.03	.04	.00
TA-V90	.00	.01	.01
TA-V100	.02	.01	.00
TA-Kmh	.00	.02	.00
CA-Txt	.00	.00	.24
CA-Cen	.00	.04	.21
CA-V10	.00	.00	.04
CA-V20	.00	.00	.03
CA-V30	.00	.00	.07
CA-V40	.00	.01	.07
CA-V50	.00	.02	.03
CA-V60	.01	.00	.03
CA-V70	.00	.00	.05
CA-V80	.00	.00	.01
CA-V90	.00	.00	.04
CA-V100	.00	.00	.01
CA_Kmh	.00	.00	.00
D	.31	.04	.00
I	.27	.01	.00

(b). AD	S1	S2	S3
π	.01	.74	.25
S1	.84	.02	.28
S2	.14	.67	.03
S3	.02	.31	.69
TA-Txt	.10	.31	.00
TA-Cen	.04	.30	.15
TA-V0	.00	.01	.00
TA-V10	.00	.01	.01
TA-V20	.01	.04	.06
TA-V30	.02	.02	.00
TA-V40	.01	.06	.00
TA-V50	.03	.12	.03
TA-V60	.02	.01	.00
TA-V70	.01	.01	.00
TA-V80	.00	.02	.05
TA-V90	.00	.00	.01
TA-V100	.00	.00	.01
TA-Kmh	.00	.03	.00
CD-Txt	.02	.00	.34
CD-V	.00	.01	.32
CA-Kmh	.01	.00	.01
D	.44	.04	.00
I	.30	.01	.02

(c). DA	S1	S2	S3
π	.04	.85	.11
S1	.95	.01	.41
S2	.03	.60	.00
S3	.02	.39	.59
TD-Txt	.12	.42	.00
TD-V	.20	.45	.00
TD-Kmh	.01	.01	.00
CA-Txt	.02	.01	.27
CA-Cen	.00	.08	.27
CA-V0	.00	.00	.00
CA-V10	.00	.00	.05
CA-V20	.00	.00	.03
CA-V30	.00	.00	.09
CA-V40	.00	.00	.10
CA-V50	.00	.01	.05
CA-V60	.04	.01	.02
CA-V70	.00	.00	.06
CA-V80	.00	.00	.01
CA-V90	.01	.00	.04
CA-V100	.00	.00	.01
D	.30	.00	.00
I	.30	.00	.00

(d). DD	S1	S2	S3
Π	.02	.81	.17
S1	.88	.07	.40
S2	.10	.60	.03
S3	.02	.33	.57
TD-Txt	.14	.44	.00
TD-V	.19	.47	.02
TD-Kmh	.00	.03	.00
CD-Txt	.00	.00	.56
CD-V	.00	.04	.41
CD-Kmh	.00	.00	.01
D	.32	.02	.00
I	.35	.00	.00

Table 2. The three states Hidden Markov Models for all speedometer type combinations.

Relatively high values in diagonals of the states' transmission matrix *A*. as well as similar emission probabilities for symbols CA-Txt and CA-Cen as well as for TD-Txt and TD-V suggest the existence of a hierarchical states' structure. For instance, while performing the ***Target identification***, it is highly probable that subjects would stay in the same state in the next step. In such a case, the sub-goals of the S_2 could be described as the ***Indicator location*** and ***Reading the velocity value***. Thus, it may be assumed that participants were moving their eyes according to the spot-light principle (Posner et al., 1980) at first, and when they came across the clock-face type of speedometer they changed their visual behavior to typical to the zoom-lens model (Eriksen & James, 1986). This finding additionally supports similar conjectures put forward in Michalski (2016) and confirms that subjects may apply complex attention shifting strategies even for such relatively simple experimental tasks. Moreover, the whole process may probably be an interesting research direction and possibly modeled by means of Layered HMM (Courtemanche, 2011).

5 Conclusions

The current study results are promising. The human visual behavior analysis in the HMM perspective provides opportunities of discovering basic attention shifting strategies while operating the control panel. The performed simulations revealed the usefulness of the HMM in discovering attention states characteristic of the human-machine interaction. The obtained models have logical interpretation in categories of real experimental subtasks. What is more, the interpretations appear to be independent of the interface design details which may result in practical applications involving automatic identification of tasks performed by operators in human-machine systems.

Furthermore, such a possibility can be a basis of developing intelligent systems for interactive products and industrial machinery. The findings regarding gender differences in attentional processes can be used for examining individual discrepancies among human-machine operators. A particular area of practical applications may regard e.g. the qualifications or training effectiveness assessment.

Generally, in contrast to classic, static and deterministic scanpath analysis which is based solely on the overt attention observations, the identification of the hidden states has its origin in physiological and psychological processes related with the covert attention. Thus, the ability to look inside the human visual processing is invaluable in extending the knowledge about the human-machine interaction. This would certainly lead to better understanding of the nature of communication with interactive products.

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