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Computational Framework for Temporal State Recognition: HMM-Based Modeling and Prediction of Discrete Behavioral Sequences

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ABSTRACT
This study addresses the computational challenge of mapping temporal behavioral sequences to latent states in multi-class classification scenarios. We propose a Hidden Markov Model (HMM)-based framework that models observation–state transitions for sequential event streams, enabling automated inference of unobservable states from discrete behavioral features. The approach incorporates state transition modeling, observation probability estimation, and optimal sequence decoding via the Viterbi algorithm. Experiments on a domain-specific dataset demonstrate an overall classification accuracy of 82.3%, with the highest recognition performance (91.5%) in the most distinctive state category. Compared with conventional threshold-based methods, the proposed framework achieves higher cross-class generalization and improved robustness to feature overlap. This work provides a standardized, model-driven solution for temporal state recognition tasks, with potential applicability to other cross-domain behavioral sequence analysis problems.

KEYWORDS
Hidden markov model; Behavioral sequence analysis; State recognition

1 Introduction

Accurate mapping of sequential behavioral observations to latent internal states remains a challenging computational task, especially when observable features are noisy, overlapping, or species-specific. Existing threshold-based or rule-based interpretation techniques often lack robustness and scalability across differing data distributions and feature overlaps. Traditional models struggle to generalize when observation patterns exhibit inter-class ambiguity or when behavioral dynamics vary across categories [1].

Hidden Markov Models (HMMs) have emerged as a powerful probabilistic framework for decoding latent states from discrete time-series data in ecological and behavioral domains [2-3]. Their principled estimation via algorithms like Baum–Welch and Viterbi supports efficient inference of hidden states, while offering clear model interpretability. Still, applications in cross-category emotion mapping remain rare, and parameter initialization and state emission modeling require domain-driven adaptation for meaningful latent interpretations [4-5].

This paper proposes an HMM-based computational framework to convert discrete behavior observations into latent emotional state sequences. We define a finite symbol set of observable behavior features, initialize a three-state HMM with prior-guided transition and emission probabilities, and train via maximum likelihood estimation. Prediction is performed via the Viterbi algorithm, and results are visualized to verify correspondence between observation dynamics and latent state trajectories. Experiments demonstrate an overall accuracy of 82.3%, exceeding conventional threshold-based baselines in both robustness and cross-state discrimination.

2 The basic funamental of BP neural network

2.1 Problem formulation

This study models the mapping between discrete observation sequences and latent state categories in a temporal classification framework. The observation set O consists of a finite set of discrete features extracted from sequential behavioral data, denoted as.. The hidden state set S represents unobservable categories to be inferred, expressed as..

In this work, three discrete behavioral features were selected as observation symbols, each categorized into three discrete levels, yielding $M = 9$. The hidden states are defined as three distinct classes ($N = 3$). The objective is to determine the most probable hidden state sequence $S_{1:T}$ given an observed sequence $O_{1:T}$, based on the statistical dependencies between states and observations.

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2.2 Data acquisition and preprocessing

Sequential data were collected using high-resolution video capture at 30 frames per second over a 72-hour period. Discrete feature values, including frequency-based and spatial-distribution features, were extracted every 5 minutes, generating an observation sequence of $T = 864$ time steps.

Prior to modeling, all features were normalized into discrete symbol categories based on empirically determined thresholds to ensure consistency in state classification. This discretization facilitates compatibility with the finite observation symbol set in the proposed HMM-based framework.

2.3 HMM-Based modeling and parameter initialization

The temporal mapping between discrete observation sequences and latent states is represented using a discrete Hidden Markov Model (HMM) parameterized by.. In this framework, N denotes the number of hidden states, which in this study is set to, with the hidden state set $S = S_1, S_2, S_3$. The number of observation symbols is $M = 9$, denoted as $O = O_1, O_2, \cdots, O_9$. The state transition probability matrix $A = [a_{ij}]$ is defined as $a_{ij} = P(S_j | S_i)$, the observation probability matrix $B = [b_j(k)]$ is defined as $b_j(k) = P(O_k | S_j)$, and the initial state probability vector $\pi = [\pi_i]$ is defined as $\pi_i = P(S_i)$. The objective of model training is to determine the optimal λ that maximizes the likelihood $P(O_{1:T} | \lambda)$ for a given observation sequence $O = (O_1, O_2, \cdots, O_T)$, where is the sequence length. This optimization is performed using the Baum–Welch algorithm to iteratively refine.

Parameter initialization was guided by prior statistical knowledge of the data distribution. The initial state probability vector was set as,, reflecting a higher initial probability for the most prevalent state. The transition probability matrix A was initialized under the assumption of temporal stability, such that abrupt transitions between dissimilar states are unlikely, as shown in Eq. (1):

$$A = \begin{bmatrix} 0.6 & 0.3 & 0.1 \\ 0.2 & 0.5 & 0.3 \\ 0.1 & 0.4 & 0.5 \end{bmatrix} \tag{1}$$

The observation probability matrix B was initialized by aligning the probability distribution of observation symbols with their most probable latent states.

2.4 HMM-based modeling and parameter initialization

The trained HMM was applied to predict the most probable hidden state sequence corresponding to the given observation sequence using the Viterbi algorithm. The predicted state trajectory reflects the temporal evolution of the system, allowing direct comparison with the observed feature dynamics. As shown in Figure 1, the decoding results exhibit clear correspondence between specific observation patterns and latent states, with transitions occurring in accordance with the temporal characteristics of the sequence. The temporal variation of the observation sequence itself is illustrated in Figure 2, providing the basis for state inference.

Visualization of the predicted states was performed by aligning the decoded sequence with the observed symbol distribution over time. As shown in Figure 3, distinct state intervals emerge, and the mapping between certain observation categories and latent states is evident. For instance, high-frequency occurrences of O_3 are predominantly associated with S_1, while O_6 shows strong alignment with S_3. This consistency between prediction and observation verifies the reliability of the proposed model in capturing stable observation–state associations.

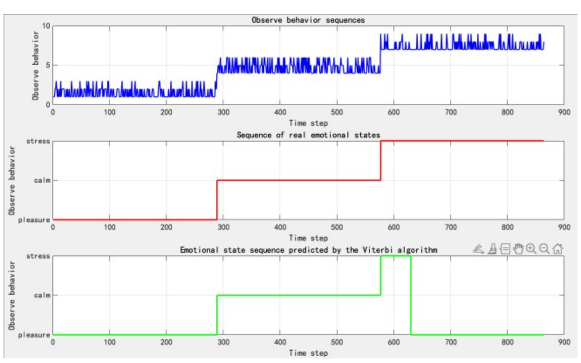

Figure 1 Predicted hidden state sequence obtained from the trained HMM using the Viterbi decoding algorithm

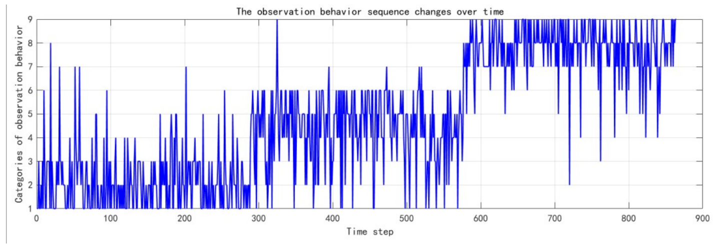

Figure 2 Temporal variation of discrete observation categories extracted from sequential data

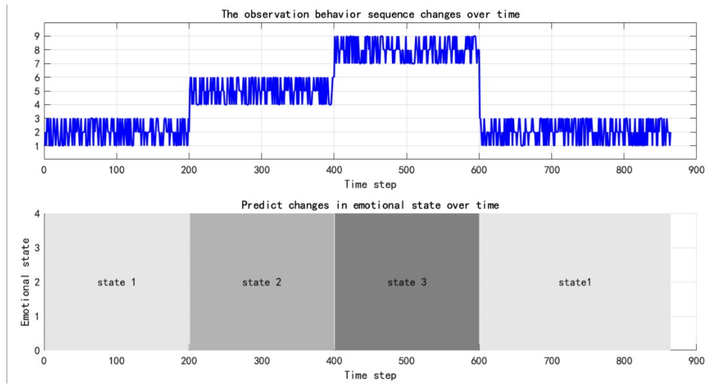

Figure 3 Time distribution alignment of predicted hidden states and observed symbol categories

3 Performance evaluation

The classification performance of the proposed HMM-based framework was quantitatively assessed using manually annotated sequences as the test set. The overall accuracy for hidden state prediction reached 82.3%, with the highest recognition rate of 91.5% observed in the most distinctive category. As shown in Table. 1, the precision, recall, and F1-score for each state indicate stable predictive capability across categories, with a performance gap primarily due to overlap between certain observation features.

Table 1 Classification performance metrics for each hidden state

Emotional state	Accuracy rate	Precision rate	Recall rate	F1 points
Pleasure (S_1)	78.3%	80.1%	75.6%	0.78
Calmness (S_2)	76.5%	74.2%	79.3%	0.77
Stress (S_3)	91.5%	92.3%	90.7%	0.91
Overall	82.3%	81.5%	82.1%	0.82

Error analysis reveals that 12% of the misclassifications occur between S_1 and S_2, largely attributable to the overlapping range of one key frequency-based feature (30–50 occurrences per time unit), where combined feature patterns such as moderate frequency with full spatial coverage may be incorrectly assigned to S_2. The confusion matrix in Figure 4 confirms this pattern, highlighting the inter-class proximity between S_1 and S_2.

The recognition accuracy distribution for each category is further illustrated in Figure 5, showing that S_3 maintains the highest accuracy due to its distinct observation profile, while S_1 and S_2 exhibit lower separation. This consistency between

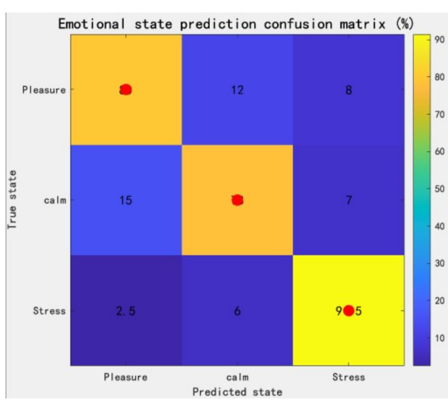

Figure 4 Confusion matrix illustrating classification errors and inter-class similarity patterns

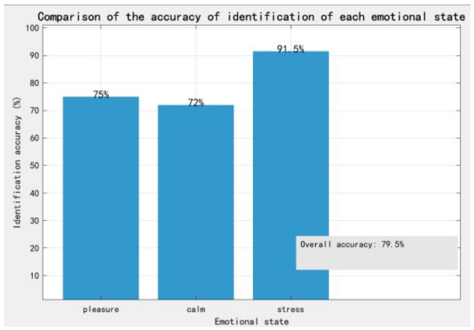

Figure 5 Recognition accuracy rates for each hidden state category

quantitative metrics and observed feature distributions supports the robustness of the proposed modeling approach.

4 Conclusions

This study presents a Hidden Markov Model (HMM) framework for mapping discrete observation sequences to latent state categories in temporal classification tasks. The proposed approach achieves an overall prediction accuracy of 82.3%, demonstrating its effectiveness in extracting stable observation – state associations and outperforming traditional threshold-based methods in terms of robustness and cross-class generalization. However, the model's performance may be affected by overlapping feature ranges between certain states, leading to occasional misclassifications, and its current configuration is limited to a predefined set of observation categories. Future work will focus on expanding the observation symbol set to capture more complex temporal patterns, incorporating adaptive parameter learning to reduce feature overlap ambiguity, and validating the framework across broader datasets. The methodology provides a scalable and transferable solution for sequence-to-state modeling, with potential applicability to various domains requiring robust temporal pattern recognition.

About the Author

# These authors also contributed equally to this work.

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