Unsupervised Human Fatigue Expression Discovery via Time Series Chain

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Abstract

Fatigue manifests as a multifaceted human condition involving both psychological and physiological aspects. It is characterized by a diminished capacity to perform tasks effectively, potentially resulting in negative emotional states, errors in passive or active tasks, and even medical emergencies. There is a growing interest and practicality in continuous monitoring to identify fatigue during extended work periods. Despite the importance of fatigue detection, it is very challenging to build a model in practice due to limited data and a diverse set of sensor modalities. In this paper, we propose an unsupervised pipeline to address the challenge of fatigue detection from video streams in a challenging realistic environment. Specifically, we propose an effective fatigue expression discovery framework by first extracting key landmark points (e.g., shoulder joint, mouth) from video streaming data, then identifying evolving behavior patterns with time series chain, an effective high-order time series primitive, to discover precursors for potential human fatigues. To demonstrate the effectiveness of our proposed framework, we show that our framework can detect signs of fatigue using video data captured in real-world fatigue scenarios.

1 Introduction

Human work and recreational activities nowadays have increasingly become more sedentary, inadvertently jeopardizing postural health. The average US adult spends 9.5 hours in sedentary behavior [15], with leisure activities constituting 47% of this sedentary time. This sedentary trend extends even to physically demanding occupations like construction work, exacerbating risks associated with postural health, leading to serious long-term health effects such as spinal dysfunction, muscle fatigue, and joint degradation. The transition to remote work environments has further accentuated these challenges, as workers often find themselves in sub-optimal ergonomic setups without adequate tools to support proper posture – a factor contributing to a reported 70% prevalence of musculoskeletal discomfort in certain populations [18].

Despite the importance of postural health, detecting signs of fatigue poses significant challenges in practice. Fatigue is a subjective experience, making it difficult to generalize [10]. Additionally, humans often lack self-awareness over their posture while working, an issue compounded by the subtlety of most postural changes. Existing approaches for fatigue detection primarily rely on supervised classification models employing computer vision techniques [10, 7, 4] or sensors invaded by humans [9, 3]. Some other approaches focusing on using invasive methods such as biosensors or other expensive devices [1, 22, 16]. However, these methods necessitate intensive effort, invasive, or expensive devices from the individual subjects to recognize signs of fatigue in their bodies. Moreover, these approaches typically lack the suitability for long-term monitoring vital for real-world practicality.

This paper presents an unsupervised pipeline designed to address the challenge of detecting fatigue from video data in realistic environments. The proposed framework can identify expressions related to fatigue. Initially, key landmark points such as the *shoulder joint* and *mouth* are extracted from the video streaming data using pose landmark detection. Subsequently, evolving behavior patterns are identified using time series chain–an effective high-order time series primitive–to uncover precursors indicative of potential human fatigue. We demonstrate the efficacy of our framework in detecting signs and expressions of fatigue using video data collected from real-world fatigue scenarios.

2 Related Work

As technological advancements continue to evolve and the capabilities of computer vision strengthen, there emerges an increasing interest and practicality in the continuous monitoring of subjects. This monitoring aims to detect various issues, including medical emergencies, emotional states, and the accurate execution of passive or active tasks [2, 14, 17].

Fatigue is a complex human state, either psychological or physiological, marked by expressions wherein humans possess a reduced ability to conduct tasks. Prior work mostly have been formulated the problem as a classification problem for various types of fatigue (e.g., fatigue from manual material handling tasks, fatigue from running) using classical and deep machine learning models in a supervised manner [10, 4]. Lambay et al. [10] constructed a recurrent neural network model for clas-

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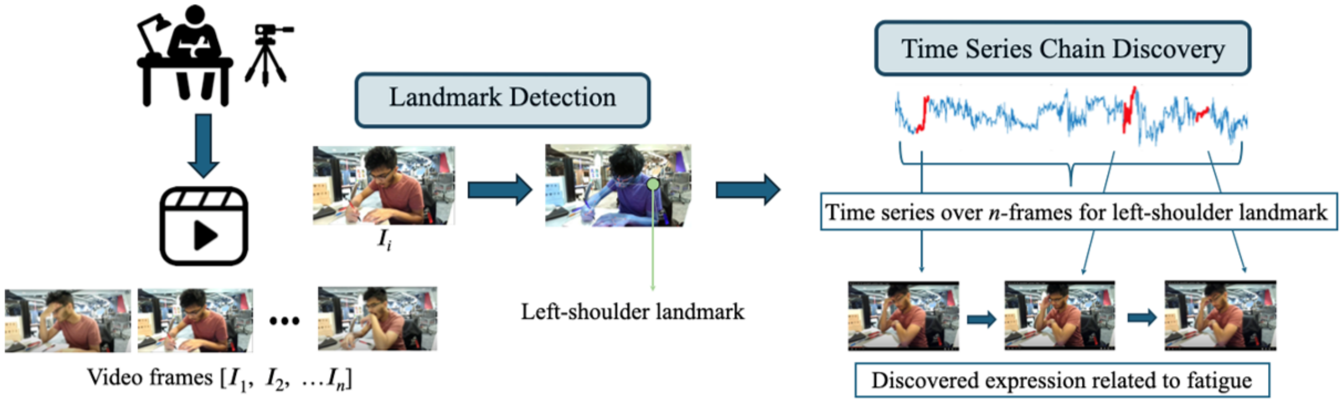

Figure 1: Video collection in an ergonomic setting followed by *10 fps* frame extraction with pose landmark detection to extract the 3D spatial coordinates of key landmark points. Spatial data is then analyzed by robust time series chain discovery to identify signs of fatigue in discovered video timestamps.

sifying human physical fatigue. Their model utilized time series data gathered from an inertial measurement unit and a heart rate sensor. Chang et al. [4] analyzed several supervised deep models for the classification of levels of fatigue in human runners. Karvekar et al. [7] developed supervised models to classify the levels of human muscle fatigue into four classes including *no-fatigue, low-fatigue, medium-fatigue, and strong-fatigue* based on the motion signals collected by a smartphone. However, these methods often rely on large amount of labels, and hence require large amount of labeled data to perform fatigue detection, which is not always practical. To address this issue, in this work, we develop an unsupervised method for detecting human physical fatigue-related expressions by observing the human subjects in a video without extracting the subject's motion signals from a smartphone or any other health-monitoring device. Our method can automatically detect the presence of human fatigue-related expressions such as *yawning*, *eye rubbing*, and *head tilting* using recent time series chain algorithms.

Time series chains [23] are a set of subsequences that are used to capture the evolvement of events over time in a dataset and have been widely utilized in different domains such as manufacturing, medicine, and finance [23, 20, 6, 21]. Zhu et al [23] proposed the first time series chain definition with a bi-dimensional time series chain and reported the longest time series chain as the best chain detected in the data. Imamura et al. [6] proposed a significantly less strict version of the time series chain using only a one-direction chain and introduced a score and filtering strategy to identify the best chain. Zhang et al. [20] designed a time series chain method for two disjoint time series to allow finding time series chains with missing time gaps by monitoring in between. Zhang et al. [21] proposed a robust time series chain method to improve time series robustness and chain quality. Most of application of time series chain focus on monitoring sales [12], manufacturing [20], animal behaviors [23]. None of the above papers have been used to analyze video data or detect fatigue. To the best of our knowledge, we are the first paper exploring the application of the time series chain method to discover unsupervised evolving behavior in video data.

3 Preliminaries Related to Time Series

Before exploring time series chain discovery, it's essential to define what time series data and its related terms are given its use in analyzing evolving patterns.

Time series T is a vector consisting of ordered real numbers, where $T = [t_1, t_2, t_3, \cdots, t_n]$ and n is the length of T.

Subsequence $T_{i,m}$ is a continuous subset of values from T, starting at position i to position $i + m - 1$ where m is the length of $T_{i,m}$. Formally, $n >> m$ and $1 \leq m \leq n - m + 1$.

Next we describe Z-normalized Euclidean Distance, which is used to compare subsequences of time series. **Z-normalized Euclidean Distance** D_z of subsequences $T_{i,m}$ and $T_{j,m}$ are computed as:

$$D_z = \sqrt{\sum_{l=1}^{m} \left(\frac{t_{i+l-1,m} - \mu_{i,m}}{\sigma_{i,m}} - \frac{t_{j+l-1,m} - \mu_{j,m}}{\sigma_{j,m}} \right)^2},$$

Where $\mu_{i,m}$, $\sigma_{i,m}$ and $\mu_{j,m}$,$\sigma_{j,m}$ are the means and standard deviations of $T_{i,m}$ and $T_{j,m}$ respectively.

Z-normalized distance is very important to time

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series comparison. Various of previous work [8, 19, 5] pointed out that normalization is essential to ensure that the comparison focuses on shape rather than scale and variation difference.

Time Series Chain is a set of subsequences $TSC = [S_{C_1}, S_{C_2}, S_{C_3}, \ldots, S_{C_m}]$ where $C_1 > C_2 > \ldots > C_m$, where S_{C_i} and $S_{C_{i+1}}$ are similar and S_{C_1} and S_{C_m} are having large distance.

Time series chain is an important technique to capture the evolving patterns in time series. We will talk about more in the next section.

4 Proposed Method

We present a technique for the automatic discovery of unsupervised evolving behavior within a video. Initially, we capture the sequence of frames from the video at a fixed frame rate. Subsequently, key points are detected within each frame. Finally, evolving behaviors are extracted from the time series associated with each key point across all frames. Our methodological pipeline is illustrated in Figure 1, with a detailed discussion of each component provided in subsequent sections.

4.1 Pose Landmark Detection Let's denote a video $\{I_1, I_2, ..., I_n\}$, where I_i is the i^{th} image frame and n is the total number of frames in the video. For each image frame I_i, we detect important key points of a human subject using a pose landmark detection model [13]. As depicted in Figure 2, the model identifies **33** pose landmarks for each frame. Each landmark is denoted by a tuple $L_i^l = (x_i^l,\, y_i^l,\, z_i^l)$, where x_i^l and y_i^l represent the 2D spatial image coordinates and z_i^l represents an estimated depth coordinate relative to the corresponding 3D environment where the image was taken for l^{th} landmark in i^{th} image frame. We accumulate each component over the entire video of N frames to construct the time series for individual pose landmarks. For example, by leveraging the l^{th} pose landmark of the video, we can construct three time series as follows:

$$X^l = [x_1^l, x_2^l, x_3^l, \cdots, x_n^l]$$

$$Y^l = [y_1^l, y_2^l, y_3^l, \cdots, y_n^l]$$

$$Z^l = [z_1^l, z_2^l, z_3^l, \cdots, z_n^l]$$

Each of these time series can be used to find evolving behaviors using robust time series chain discovery, as elaborated upon in the following sections.

4.2 Time Series Chain Discovery We will first describe some time series chain-related definitions, then formally describe the time series chain discovery method.

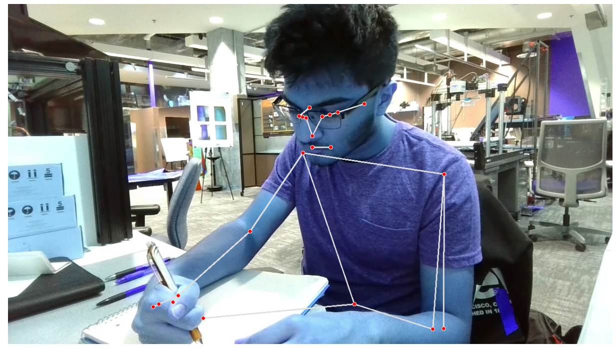

Figure 2: Detected pose landmarks, depicted by red circles, are illustrated in a sample image frame from a video. Best viewed in color.

Time Series Chain (TSC) is a finite ordered set of subsequences where T_{C_i} is very similar to $T_{C_{i+1}}$. Formally, $TSC = [T_{C_1}, T_{C_2}, T_{C_3}, \cdots, T_{C_l}]$, where l denotes the total number of nodes or subsequences in a chain. We aim to find an ordered set of subsequences among the time series that captures the evolving trend within our data. Time series chains are useful for capturing patterns that are evolving or experiencing gradual changes, where nodes in a chain may not be identical but are sufficiently similar to be significant. We can capture specific features using anchored time series chains based on a subsequence where that feature might be present.

Time Series All-Chain Set is a set of time series chains. To form time series chains, we leverage the nearest neighbors to create a set that changes incrementally starting from the end of the time series. The Incremental Nearest Neighbor Set is created from the RNN of the current subsequence we are observing at $T_{i,m}$.

Incremental Nearest Neighbors Set ($INNS$) of $T_{i,m}$ is a set containing subsequences where the $d(T_{i,m}, T_{j,m}) < d(T_{i,m}, T_{j,m})$ for all k when $j < k \leq i$. A key component to time series chains is **Critical Nodes**, which are subsequences that belong to the $INNS$ of their LNN.

Critical Node CN is where a subsequence in T is considered a CN if $T_{i,m}$ is in $INNS(LNN(T_{i,m}))$.

$INNS$ and CN are employed in TSC22 to construct chains that are flexible with the nodes included in the chain, avoiding unrelated nodes to the pattern.

Relaxed bi-directional time series chain (TSC22) is a finite ordered set of nodes or subsequences where $C_1 > C_2 > C_3 > \cdots > C_l$ that meet the following conditions:

1) for any $1 \leq i < l$, $LNN(T_{Ci}) = T_{Ci+1}$
2) the starting node, $T_{C1} \in CN^T$
3) for any $1 < i \leq l$, $T_{Ci} \in INNS(T_{Ci})$

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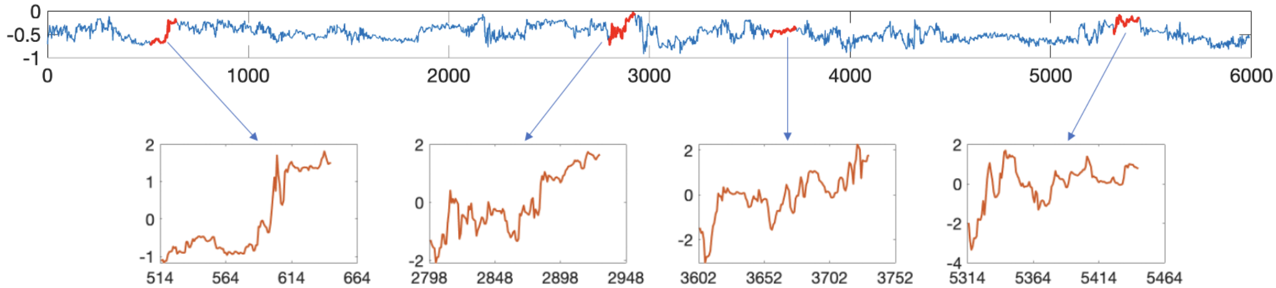

Figure 3: Fatigue patterns by time series chain algorithm detected on landmark 10 (right mouth) location from a video data.

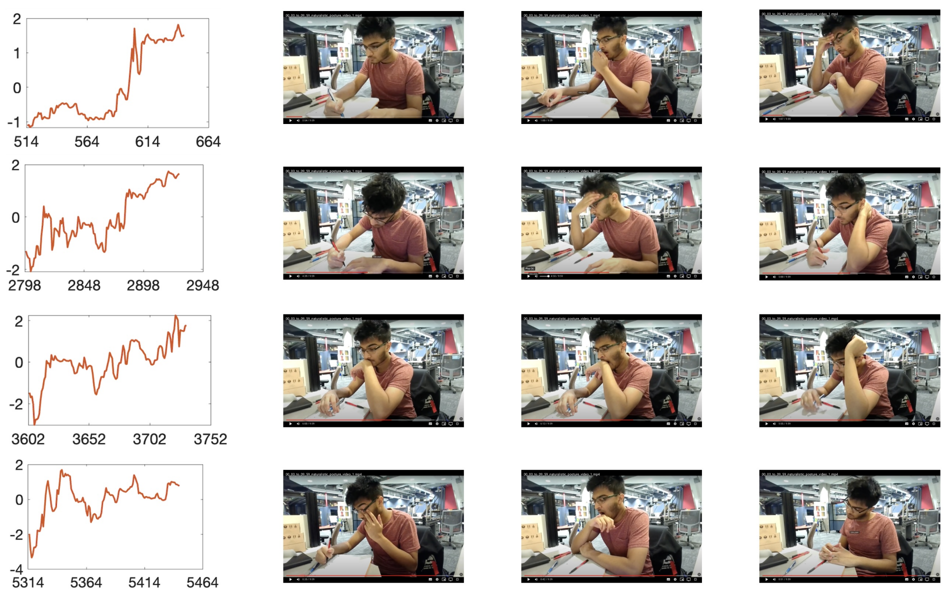

Figure 4: Subplots from time series chain with the corresponding video captures for landmark 10 (right mouth). A sequence of signs of writing and yawning with posture change over time was detected by the proposed time series chain.

For a subsequence to be considered part of a TSC, according to TSC22, it must meet the conditions in the definition above. In conditions 1 and 2, the starting node in a chain is considered a CN, and for every node in the chain up to the last one, its succeeding node is its LNN. In condition 3, the CN after T_{Ci} must be in the $INNS$ of T_{Ci}. These conditions help in forming more robust chains that could hold meaningful information.

4.3 Chain Detection Algorithm We propose to use the Robust Time Series Chain Algorithm [21] to detect the evolving fatigue patterns in the landmark time series obtained in Section 4.1. TSC22 starts with computing the LNN and $INNS$ by using the STUMP algorithm [11] on all the corresponding subsequences to find all the critical nodes in the times series, then discovering chains starting from reverse order by marking the visited critical nodes on a boolean vector and skipping marked nodes to avoid repeats. After going through all the nodes, the sub-chains are all stored corresponding to each discovered chain.

4.4 Chain Ranking We apply the ranking criteria in Robust Time Series Chain [21] to select the best time series chain based on the all-chain set to obtain the optimal chain. We first compute the **Effective length** metric L_{eff}, which measures both divergence and graduality at the same time:

$$L_{eff} = \lfloor d(S_{C_1}, S_{C_m}) / \max_{1 \leq i \leq m-1} d(S_{C_i}, S_{C_{i+1}}) \rceil, \tag{4.1}$$

where $\lfloor . \rceil$ denotes rounding to the nearest integer.

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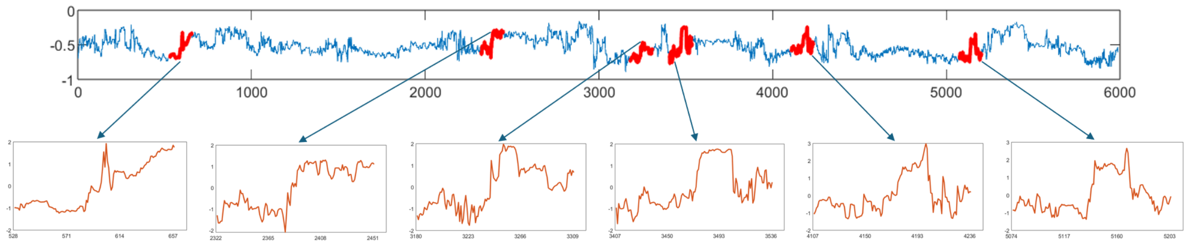

Figure 5: Fatigue patterns by time series chain algorithm detected on landmark 11 (left shoulder) location from a video data.

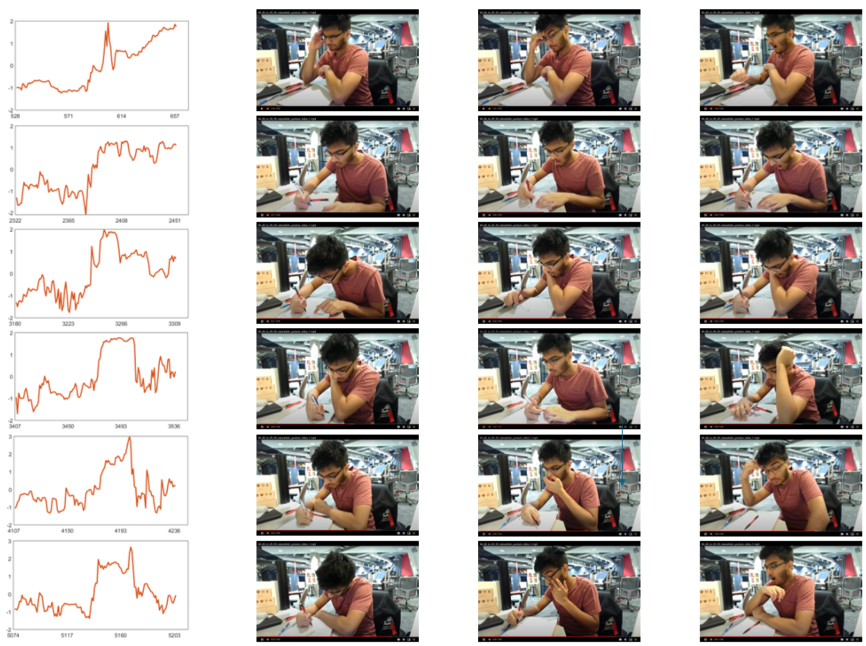

Figure 6: Subplots from time series chain with the corresponding video captures for landmark 11 (left shoulder). A sequence of signs of writing - yawning - rubbing eyes with posture change over time was detected by the proposed time series chain.

Then we compute the **Correlation Length** L_{corr} as follows:
(4.2)

$$L_{corr} = \sum_{i=1}^{m-1} |Corr(S_{C_i}, S_{C_{i+1}})| Corr(S_{C_i}, S_{C_{i+1}}).$$

where $Corr(.) \in [-1, 1]$ is the Pearson Correlation Coefficient of the z-normalized subsequences. The correlation length prefers long chains with similar consecutive subsequences.

5 Experiment

5.1 Dataset and Experimental Setup We collected three videos of approximately ten minutes in duration, wherein sedentary human subjects seated in ergonomic environments were simply asked to record themselves working. A built-in camera on the subject's computer was used to record videos at a resolution of 720p. This webcam was positioned at an angle of approximately 45 degrees in front of the subject and remained fixed on a desk throughout each video to ensure the comprehensive coverage of the subject's *torso, arms, hands,* and *facial expressions.* In two of these recorded videos, subjects were instructed to work while experiencing exhaustion as an additional condition. This was done to investigate whether our method of discovering time series chains could discern the subjects' level of energy, emotional state, and activity. Key events relating to all these variables were annotated for each video before processing. We preprocess the video offline by extracting images at a rate of 10 frames per second.

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Approximately 10,000 frames were extracted for each of our 10-minute videos. We will examine the result and verify if the detected behavior patterns are signs of fatigue with human knowledge.

Using the approach outlined in Section 4.1, we extracted 33 pose landmarks for each video. Then, we used our time series chain discovery algorithm on a random subset of these pose landmarks, focusing on the upper body of the subject, including *left-eye, right-eye, left-mouth, right-mouth, left-shoulder,* and *right-shoulder*. The time series corresponding to the depth coordinates, i.e., $Z^l = [z^l_1, z^l_2, z^l_3, \cdots, z^l_n]$, was chosen for experimentation, particularly due to their higher sensitivity compared to other dimensions[1].

A sub-sequence length of 130 was used, representing an action length of thirteen seconds in the video. The acquired collection of frames from the most optimal set of chains uncovered through the chain ranking criteria 4.4 was then analyzed to discover the specific behavior pattern that the time series chain revealed.

5.2 Empirical Results We apply the robust time series chain discovery algorithm to our time series data generated by Landmark 10 and Landmark 11 with a subsequence length of 130, representing an action length of 13 seconds in the approximately 10-minute video of a tired student working. Fig. 3 and Fig. 5 show the time series chain discovered with the highest score for Landmark 10 and 11 respectively with Fig. 4 and Fig. 6 showing the corresponding frames in the video for each Landmark. We observe an evolving pattern in the sequence indicative of fatigue progression from the action of writing starting with the subject writing, yawning, and rubbing their left eye, transitioning to the student writing, touching their chin, and then putting their head down in the time series data for Landmark 10 4.

The time series data for Landmark 11 further showcases the discovery of signs of fatigue with the spikes in the first, second, and third discovered chains all corresponding to yawning while writing in the video 6. While the peak in the first chain corresponds to a short period of yawning as the student covers his mouth with his hand, we observe a more prolonged period of yawning in the peaks of the second and third chain as the student writes, highlighting the increased fatigue of the subject as the video progresses. Further, notably more subjective, signs of fatigue are observed in the spikes of the fourth, fifth, and sixth discovered chains with the student rubbing his forehead, nose, and eyes in tiredness. These experiments demonstrate our method's ability to not only identify expressions of fatigue using time series data generated from key landmark points but also how the fatigue of a subject evolves over time.

6 Conclusion

In this paper, we propose an unsupervised method to tackle the problem of discovering expression patterns for human physical fatigue in challenging situations. Particularly, we propose to use time series chain, an efficient high-order time series primitive, to capture the evolving action over time to discover precursors for the physical fatigue of a human subject in the landmark time series converted from a single video data. Our method can be performed in a low-cost environment. To demonstrate the effectiveness of our proposed framework, we show our method can discover fatigue expression with video data recorded in real-world physical fatigue situations.

[1] https://developers.google.com/ml-kit/vision/pose-detection#z_coordinate

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