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A Two-stage Gait Analysis Using Interval-based Sequential Pattern Mining

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Abstract. Artificial Intelligence (AI) has recently experienced a significant rise in its implementation, as evidenced in several industries, such as telerehabilitation. Regarding the digital transformation in telerehabilitation, some companies have already utilized machine learning techniques to analyze the dataset collected via sensors or cameras and then support distance medical experts in diagnosing through the Internet. This research proposes a novel two-stage data mining framework combining gait analysis and interval-based sequential pattern mining. Potential problems or diseases are discerned in the first stage by analyzing gait videos captured from a camera. A series of walking postures captured frame by frame can be transposed into a sequence of events. For instance, a particular frame might depict a gait indicative of a possible Parkinsonian gait. Since these events are recorded temporally, a series of similar events can be merged to form an interval-based event, described by its starting and ending points. Subsequently, the second stage involves extracting and recognizing patterns from a dataset of interval-based temporal sequences through sequential pattern mining. This preliminary experiment collected twenty real-life samples and corroborated the usefulness of the proposed model.

Keywords: Artificial Intelligence, Data Mining, Gait Recognition, Sequential Pattern Mining, Interval-based Sequence

1. Introduction

There have been significant advances in artificial intelligence (AI) in recent years [1, 2]. One of the most notable developments has been the emergence of deep learning [3], which has led to breakthroughs in areas such as computer vision [4], and natural language processing [5]. These techniques have been applied in various applications, including faster preliminary diagnoses [6] and telerehabilitation [7].

In telerehabilitation, gait analysis [8, 9] is a non-invasive medical procedure. Gait analysis involves observing various gait characteristics, such as angles, time, range of motion, angles of joints, etc. Gait analysis can be performed using high-tech instruments like wearable sensors [10] or motion-sensing technology (e.g., Microsoft Kinect [11]), which provide objective measurements of gait parameters.

This study primarily aims to use a particular data mining technique, interval-based sequential pattern mining, to analyze gait videos. If multiple gait videos are collected, valuable information can be discovered from them. First, each gait video can be split into many frames (images). A deep learning-based module could identify each image as a possible symptom. Take Fig. 1 as an example. The subject's footsteps in the image were considered possible Hemiplegic gait. Because the images in a video are arranged in chronological order, their identification results are also placed in the same order. This kind of list is called a temporal sequence, in which their temporal relationships decide the ordering of the items. For example, three kinds of gaits are identified as three possible symptoms and arranged as a temporal sequence: $(A \rightarrow B \rightarrow C)$, where the arrangement of A, B, and C refers to the succeeding symptom happening after the preceding one. Assume a system has collected a database of many temporal sequences converted from gait videos. For example, if we collect three sequences, $(C \rightarrow B \rightarrow A)$, $(C \rightarrow A \rightarrow B)$, and $(B \rightarrow C \rightarrow A)$. The order of $(C \rightarrow A)$, repeatedly appearing in these three sequences, is called a frequent sequence. The frequency of

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occurrence is one of the indicators of importance. Researchers have used frequent temporal sequences as information representations to discover implied information from human beings' temporal actions.

Fig. 1: A subject's gait was classified as a possible Hemiplegic gait.

However, if consecutive frames in a video are determined to be of the same category, we can concatenate them and use a time interval to describe them. Take Fig. 2 as an example. If a series of subject's consecutive gaits is judged to be "normal" from the 0^{th} second to the 3^{rd} second, this creates a time-interval of normal gait with a starting time-point (at the 0^{th} second) and an end time-point (at the 3^{rd} second). This study considers the relationship between gait and time and regards a gait as a one-dimensional temporal event with a beginning- and ending time points. Each event (e) has a time interval with its beginning time-point (e^+) and ending time-point (e^-). (For example, the beginning of event C is C^+.) As a result, the consecutive "normal" gaits in Fig. 2 can be written as $s = (N^+(0) < N^-(3))$, where the numbers inside the parentheses represent time points. On the other hand, real-world gaits are complex and can have different characteristics. Sometimes, gaits can be judged simultaneously as different types of symptoms (of a disease). See Fig. 2. The frames (in a gait video) between the 2^{nd} and 5^{th} seconds is determined to be Parkinsonian (P). The total sequence can be written as $s = \left(N^+(0) < P^+(2) < N^-(3) < P^-(5)\right)$, arranged by their orders of time-points. If we only consider the relationships among the beginning and ending time points [12], the interval-based temporal sequence in Fig. 2 can be written as $s = \left(N^+ < P^+ < N^- < P^-\right)$, which represents an "overlap" relationship.

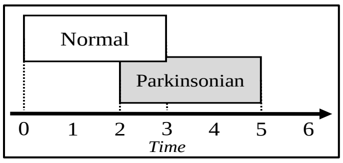

Fig. 2: An example illustrating an interval-based temporal sequence and their "overlap" relationship.

If we can collect many gait videos, interval-based sequential pattern mining can be applied to discover valuable information. The contributions of this preliminary study can be expected in two points:

- A real-world dataset was used to demonstrate our framework.
- Although temporal sequences are a widely used form of knowledge, to the best of the authors' knowledge, no study has applied the idea to gait analysis, mainly since deep learning-based image recognition technology has only emerged in recent years. A novel framework, *Interval-based Sequential Pattern Mining on Gait Analysis (ISPM-GA)*, is proposed in Section 3.

Before discussing our model, providing the research background may be necessary. We review state-of-the-art studies related to gait analysis and the recent development of Temporal pattern mining (TPM) in Section 2. Our novel framework is proposed in Section 3.

2. Literature Review

Gait analysis involves measuring and analysing human movement, commonly used in clinical settings for diagnosing and treating musculoskeletal and neurological conditions, such as Parkinson's disease [13] and other diseases in the earliest stages[14]. Two methods for enhancing gait analysis are wearable devices and computer vision processing [13]. Computer vision techniques, particularly articulated body pose estimation, are used to determine joint positions and orientations from images or videos. Deep learning-based approaches [14, 15] using convolutional neural networks (CNNs) have shown promising results. Additionally, 3D cameras like Microsoft Kinect can provide accurate 3D information, improving gait analysis accuracy [11, 16]. Sequential Pattern Mining (SPM) is a technique derived from frequent itemset mining, aiming to identify frequently purchased items in a dataset[17]. The Generalized Sequential Patterns (GSP) algorithm [18] is a sequential version of the Apriori algorithm used in SPM. Temporal pattern mining (TPM) tasks extract knowledge from time-based datasets, with two subcategories based on the nature of events: point-based [19] or interval-based [20, 21] along a timeline.

3. The Proposed Model: Interval-based Sequential Pattern Mining on Gait Analysis

This section briefly describes our framework: *Sequential Pattern Mining on Gait Analysis (ISPM-GA).* First, the outline of *ISPM-GA*, consisting of two stages is illustrated in Fig. 3. The first stage converts the gait videos into one-dimensional interval-based temporal sequences. In the second stage, the valuable information will be explored from the sequences.

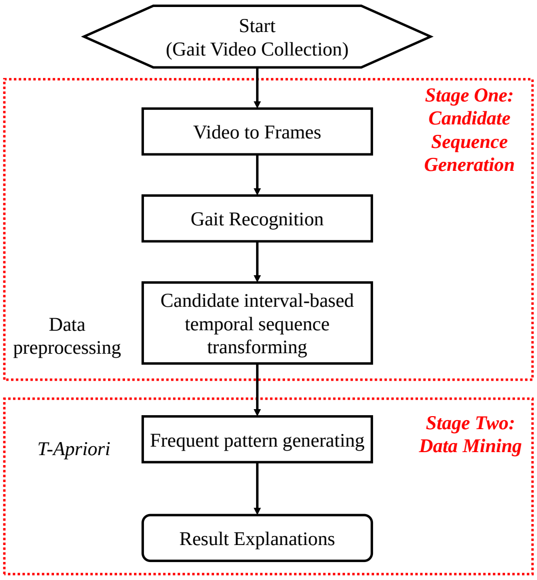

Fig. 3: The outline of the ISPM-GA framework

Assume we have collected samples from a group of subjects, $\boldsymbol{U} = \{u_1, \ldots, u_i, \ldots, u_{|U|}\}$[1], with i being the sample index. Each subject is recorded a fixed-length video, capturing their walking motion. See Fig. 4 as an example. The original video recorded by the i_{th} subject is denoted as v_i. Video v_i consists of a series of image frames, $v_i = \{f_{i1}, f_{i2}, \ldots, f_{ij}, \ \ldots, f_{in}\}$, where f_{ij} represents the j_{th} frame in v_i, and n signifies the total number of frames in v_i. A frame f_{ij} can be classified into user-defined events, $\boldsymbol{X} = \{x_1, x_2, \ldots, x_{|\boldsymbol{X}|}\}$, using a gait recognition module, $g()$. Each frame is identified as a specific event, meaning $g(f_{ij}) = e_{ij} \in \boldsymbol{X}$, where e_{ij} is the event classification for f_{ij}. The resulting conversion is a set of sequences, $s_i \in \boldsymbol{S}$, where $s_i = \{e_{i1}, e_{i2}, \ldots, e_{in}\}$, and the subscript i indicates that s_i is the i_{th} sequence in $\boldsymbol{S}$.

Example 1. Given $\boldsymbol{X} = \{\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C}\}$, which are the pre-defined events. $|\boldsymbol{X}| = \boldsymbol{3}$. A subject's walking video $\boldsymbol{v_1}$ is analyzed. Suppose only six frames are in the video. Each frame is then recognized by a module $\boldsymbol{g}()$. $\boldsymbol{g}(\boldsymbol{f_{11}}) = \boldsymbol{A}$. $\boldsymbol{g}(\boldsymbol{f_{12}}) = \boldsymbol{A}$. $\boldsymbol{g}(\boldsymbol{f_{13}}) = \boldsymbol{B}$, etc. As a result, the converted sequence is $\boldsymbol{s_1} = \{\boldsymbol{A}, \boldsymbol{A}, \boldsymbol{B}, \boldsymbol{B}, \boldsymbol{B}, \boldsymbol{C}\}$. ▩

If several consecutive frames belong to the same event, they will be transformed into an interval-based event. An interval-based event is a non-empty interval and is represented as a triple notation: $x = (x^+, x^-) = (t_x^+, t_x^-)$, where x is the event x's label; x^+ and x^- are the beginning and the ending time-points of event x, respectively. t_x^+ and t_x^- are their values. $t_x^- - t_x^+ > 0$ is the duration of the event x. $x \in \boldsymbol{X}$, where $\boldsymbol{X}$ is a set of all the events. Next, we show the form of an interval-based temporal sequence using examples.

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[1] The absolute value (|.|) represents the number of elements of a set in this article.

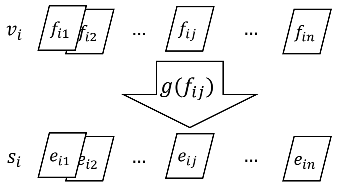

Fig. 4: The classification transformation from frames to pre-defined events.

Example 2. Suppose a converted sequence $s = (AAAABBAABBB)$, where both A and B are recognized results by the pattern recognition module, $g()$. In the s, the number of consecutive events As is four, followed by two Bs, one A, and three Bs. The sequence can be transformed to $s = \{A^+(1) < A^-(4) < B^+(5) < B^-(6) < A^+(7) < A^-(8) < B^+(9) < B^-(11)\}$, where the numbers inside the parentheses represent time-points. Since the occurrences of A at time points 7 and 8 are little, we consider that it is an overlap and thus connect it with the previous interval. The new interval-based temporal sequence becomes $s = \{A^+(1) < B^+(5) < A^-(8) < B^-(11)\}$, which shows an "overlap" relationship between the events A and B.

Thirteen types of relationships exist between two intervals, as defined below, and illustrated in Figure 5.

Definition 1 (Relationship between two events)

Given any two events: x_m and x_n, in an *its*, their conceptual temporal relationship can be described by Allen's thirteen relationships [12], as in Fig. 5: before (<), meet (**m**), overlap (**o**), start (**s**), during (**d**), finish **(f)**, equal to (=), finished by (**fi**), contained in (**di**), started by (**si**), overlapped by (**oi**), met by (**mi**), and after (>). That is,$Rel(s, x_m, x_n) \in \{<, \mathbf{m}, \mathbf{o}, \mathbf{s}, \mathbf{d}, \mathbf{f}, = \mathbf{fi}, \mathbf{di}, \mathbf{si}, \mathbf{oi}, \mathbf{mi}, >\}$. ■

Table 1: An example introducing the database of interval-based temporal relationships.

Subject	The original sequences	The interval-based temporal relationships
1	$s_1 = (A \cdots AABBB \cdots B)$	(A overlaps B)
2	$s_2 = (AA \cdots AAAB \cdots B)$	(A meets B)
3	$s_3 = (A \cdots AABBB \cdots BCCCC)$	(A overlap B, and then B meets C)
…	…	

The T-Apriori algorithm [22] is used to discover frequent patterns from interval-based temporal sequences in this study. Further information on the T-Apriori algorithm is available in [22] due to the page limitations of the conference.

4. Experimental Design and Results

In this preliminary study, 20 samples were collected using the ISPM-GA framework Fig. 3 to record participants walking along a 5-meter walkway in front of a white wall for 10 seconds. The videos were separated into individual image files, and image recognition was performed on each using an open-source module created by Kim, Kang, and Lee (Diagnosis of gait disorder by Human pose estimation2) to identify each image and classify the gait into seven possible symptoms. Next, the consecutive frames were transformed into interval-based temporal sequences (as Table 1) and then into three types of reasons ("Normal," "Brain," and "Nerve") to reduce the time complexity of the T-Apriori algorithm. Please refer to Table 2.

Table 2. Kim's module can recognize the seven symptoms and their corresponding potential causes.

No.	Type of gait	Mapping
1	Normal gait	0
2	Choreiform gait	1 Brain (Basal ganglia)
3	Diplegic gait	2 Nerve (UMN, Upper Motor Neuron)
4	Hemiplegic gait	2 Nerve (UMN, Upper Motor Neuron)
5	Neuropathic gait	2 Nerve (Peripheral nerve)
6	Ataxic gait	1 Brain (Midline cerebellar disease)
7	Parkinsonian gait	1 Brain (Basal ganglia)

[2] https://github.com/KimTaeYun02/Classification_Gait

No.	Relation	Illustration	Sequence
1	*A* before *B*	*A* *B*	$A^+ < A^- < B^+ < B^-$
2	*A* meet *B*	*A* *B*	$A^+ < A^- = B^+ < B^-$
3	*A* overlap *B*	*A* *B*	$A^+ < B^+ < A^- < B^-$
4	*A* start *B*	*A* *B*	$A^+ = B^+ < A^- < B^-$
5	*A* during *B*	*A* *B*	$B^+ < A^+ < A^- < B^-$
6	*A* finish *B*	*A* *B*	$B^+ < A^+ < A^- = B^-$
7	*A* equal to *B* (*B* equal to *A*)	*B* *A*	$A^+ = B^+ < A^- = B^-$
8	*B* finished by *A*	*A* *B*	$A^+ < B^+ < A^- = B^-$
9	*B* contained in *A*	*A* *B*	$A^+ < B^+ < B^- < A^-$
10	*B* started by *A*	*A* *B*	$A^+ = B^+ < B^- < A^-$
11	*B* overlapped by *A*	*A* *B*	$B^+ < A^+ < B^- < A^-$
12	*B* met by *A*	*B* *A*	$B^+ < A^+ = B^- < A^-$
13	*B* after *A*	*B* *A*	$B^+ < B^- < A^+ < A^-$

Fig. 5: Allen's thirteen relationships [12].

The experimental results indicate that as the minimum support threshold in the *T-Apriori* algorithm increases, the experimental time decreases, and the number of patterns generated decreases (Figure 6). Regarding the subjective interpretation of the discovered results from the *T-Apriori* algorithm, we found that $(Normal, long)$ overlap $(Nerve, short)$ is the most frequent pattern when the minimum support threshold varies. The pattern may indicate that gaits (symptoms) caused by nerve problems will be usually overlapped by normal gaits and appear for a short time.

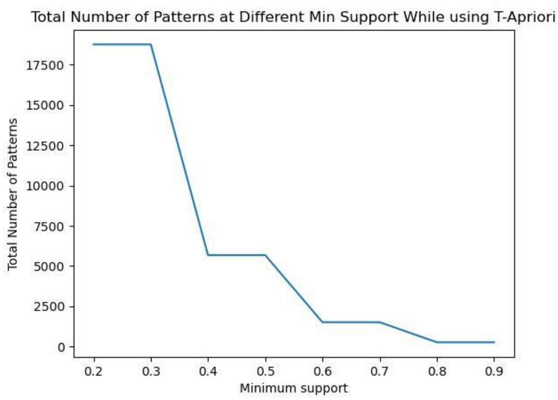

Fig. 6: The number of patterns varies as the minimum support threshold changes.

5. Summary and Future Work

Our framework integrating gait recognition and temporal pattern mining has potential in telemedicine and geriatric rehabilitation. We plan to improve the framework by collecting more real samples (particularly samples from elderly individuals), plan to employ a three-dimensional camera for improved accuracy in gait recognition. And employ unsupervised learning such as clustering to further analyze possible insights.

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