MITSUBISHI ELECTRIC RESEARCH LABORATORIES
http://www.merl.com

Time Series Segmentation with Leg Analysis for Human Motion Analysis

Imamura, Makoto; Inoue, Mao; Terada, Masahiro; Nikovski, Daniel N.

TR2019-150 December 11, 2019

Abstract

To enable automated analysis of human motion data collected by acceleration sensors, gyro senors, or motion capture devices, an approach for accurately segmenting primitive actions is required. Whereas most existing approaches use templates of basic actions such as "stand up", "walk" and "sit down", we introduce a novel problem called "structural motif discovery" that aims to find segments without templates from repetitive routine motion that consists of regularly ordered (actions?). We also propose a novel segmentation method that approximates the time series with a sequence of convex-shaped patterns by means of leg analysis, which is parameter-free and its complexity is O(N), where N is the length of a given time series. The experimental results show that our proposed method is effective for both simulation data and real data and real data from repetitive assembly operations,

International Workshop on Informatics

Time Series Segmentation with Leg Analysis for Human Motion Analysis

Makoto Imamura*, Mao Inoue*, Masahiro Terada*, and Daniel Nikovski**

*School of Information and Telecommunication Engineering, Tokai University, Japan
**Mitsubishi Electric Research Laboratories, USA
imamura@tsc.u-tokai.ac.jp

Abstract – To enable automated analysis of human motion data collected by acceleration sensors, gyro sensors, or motion capture devices, an approach for accurately segmenting primitive actions is required. Whereas most existing approaches use templates of basic actions such as "stand up", "walk" and "sit down", we introduce a novel problem called "structural motif discovery" that aims to find segments without templates from repetitive routine motion that consists of regularly ordered (actions?). We also propose a novel segmentation method that approximates the time series with a sequence of convex-shaped patterns by means of leg analysis, which is parameter-free and its complexity is $O(N)$, where N is the length of a given time series. The experimental results show that our proposed method is effective for both simulation data and real data from repetitive assembly operations.

Keywords: Time series, Segmentation, Human motion analysis, Sensor data mining, Convex-shaped pattern

1 INTRODUCTION

To enable automated analysis of human motion data such as exercise monitoring, gesture recognition, human machine interaction, and robot imitation learning, segmenting primitive actions is critical [1][2][3]. Time series segmentation is the process of identifying the temporal events of movements of interest, making a continuous sequence of time series into smaller subsequences to facilitate movement identification, modeling, and learning.

We have developed two applications of human motion analysis with acceleration sensors, gyro sensors, and motion capture devices. The application domains are factory work processes [4] and baggage lifting work [5]. In these applications, time series segmentation is critical. Therefore, we propose a novel segmentation method that approximates the time series with a sequence of convex-shaped patterns from a continuous motion sequence with leg analysis [6].

The rest of our paper is organized as follows. Section 2 describes the problem statement, our approach, and the scope of this paper. Section 3 describes our method that consists of convex feature extraction and symbolic convex approximation. Section 4 evaluates our method on one simulation and one real data sets.

2 BACKGROUND

2.1 Problem Statement

A typical method for human motion analysis is a combination of template matching by dynamic time warping (DTW) and change point detection by segmentation according to Zero Velocity Crossing (ZVC) with given general templates such as "stand up", "walk" and "sit down" [1][2][3]. However, factory worker motions are complicated and depend on the target product and the target process, so it is difficult to prepare specific templates that correspond to such motions for the purpose of analysis. Therefore, we need to deal with the problem of how to extract basic actions without templates from time series collected by sensors such as acceleration, gyro and motion capture. The type of motion targeted in this paper is a repetitive routine operation that consists of regularly ordered basic actions.

Figure 1 shows an example of a repetitive routine operation. The routine operation consists of three basic actions, which are "(a) carry a main body product from a previous process", "(b) attach a part to the main body product (action B)" and "(c) carry the main body product to the next process". Hereafter, we call a repetitive routine process a *cycle*. A cycle is important in the factory domain, because it corresponds to a process in production. If we can extract a cycle correctly, we can measure the working time of a process. The automatic measurement of each working process time for each worker helps us to find bottleneck operations, an operation error, and also possibly measure the fatigue level of the worker, which are useful for improving product efficiency.

The cycle in Figure 1 is expressed by "abbc", "abbbc" or "abc", if the action "b" repeats more than once depending on the specification of a product. By using a regular grammar, the cycle can be expressed by "a(b+)c". The problem in this paper is described by the following.

Problem: Let X be a time series that corresponding to a series of repetitive routine operations that consist of regularly ordered actions. Find a repetitive routine pattern in X and find a regular expression to represent that pattern.

Hereafter, we call the above problem *structural motif discovery*.

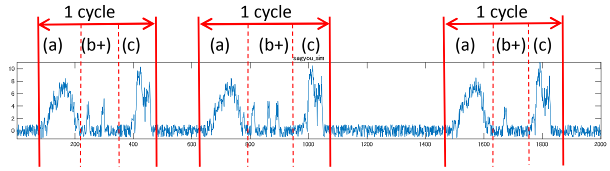

Figure 1: An example of time series with substructure

2.2 Approach

A typical existing method to solve the structural motif discovery problem is motif discovery [7][8]. Because the subsequences corresponding to the same action are similar to each other, we can find the basic actions as repeatedly occurring subsequences by means of motif discovery. However, existing motif discovery algorithms require subsequence lengths for basic actions. In our problem setting, we do not know the subsequence length of a basic action. Furthermore, the complexity order of motif discovery is $O(N^2)$ or $O(N^3)$, where N denotes the length of the time series, because of the embedded calculation of Euclidean or DTW distances.

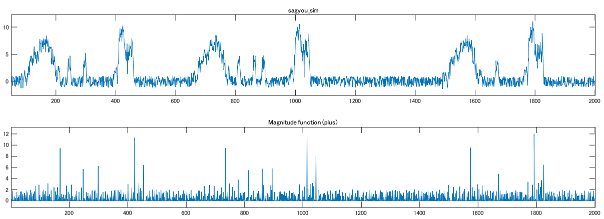

Figure 2: An example of the result by leg analysis

We investigate a novel approach to approximating a time series with a series of convex-shaped patterns by means of a leg analysis algorithm, which is parameter free and its complexity order is $O(N)$. We expect that our approach has advantages over the existing motif discovery algorithms with Euclidian or DTW distances in the following aspects.

(i) Feature extraction: The highest-cost process in solving structural motif discovery problems is the feature extraction to recognize actions. The feature extraction in our approach is convex-shaped pattern extraction by leg analysis, whereas that in existing approaches is nearest neighbor search with Euclidian distance. Our computational complexity is O(N), vs. $O(N^2)$ of existing methods.

(ii) Parameter selection: A required parameter of our approach is the magnitude level of a convex-shaped pattern, whereasexisting methods require the subsequence length. Though the subsequence length varies for each basic action, the magnitude level can be expected to be more independent from each basic action, because the magnitude level depends on small primitive human motions that construct a basic action. This hypothesis is perhaps not self-evident, so it requires exhaustive experiments to test it.

(iii) Parameter optimization: When we try another parameter value, our approach does not need recalculation for feature extraction, which existing methods do. The difference is that leg analysis is parameter-free so that extracted features are also independent of this parameter. Our approach is easier to try for various parameter values than existing methods.

(iv) Robustness: Our approach approximates time series with convex-shaped patterns, while existing methods treat a strict shape by Euclidean distance. This difference has pros and cons. With regard to robustness to the noise in time series, our approach has the possibility to be superior. Structured motif discovery requires a huge combinatorial calculation cost, therefore an approximation approach has the possibility to be able to prune search trees efficiently. On the other hand, with regard to the precision of pattern recognition, existing methods might be superior to our method. This hypothesis also requires exhaustive experiments to test it.

2.3 Scope

The purpose of this paper is an early stage trial to confirm if our approach can provide an insight into the structural motif discovery problem. We formulate our approach and evaluate it one two examples: one simulation data set and one real data set. A quantitative evaluation on exhaustive experiments and parameter optimization methods are left as future work.

3 METHOD

3.1 Convex Feature Extraction

Leg analysis [6] provides a convex pattern extraction algorithm to extract every convex-shaped pattern which has local maximal or local minimum values. A convex-shaped pattern is characterized by a 4-tuple ("peak position", "magnitude", "left terminal", "right-terminal"). In a precise definition, we should treat a trapezoid as a convex-shaped pattern in the case when its peak is a flat region, but here we only show a simplified definition of it for readers to understand the key idea of our approach. The precise definition and a detail algorithm for its computation are covered by the original paper [6].

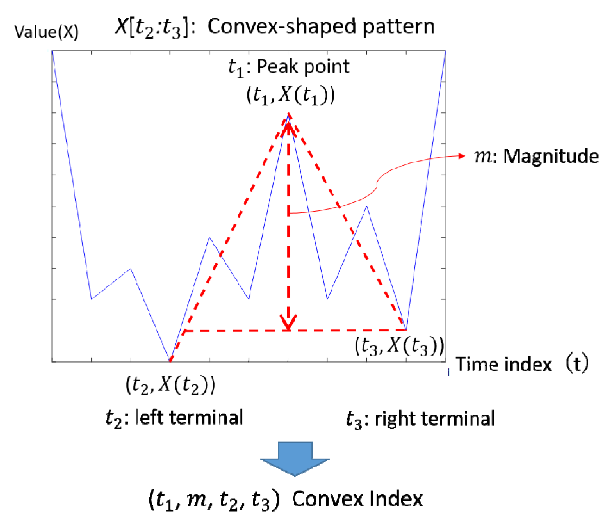

Figure 3: An example of a convex-shaped pattern and its convex index

We define a time series, a subsequence, a convex pattern index and a convex profile as a data-structures to describe a convex-shaped pattern. Figure 3 shows an example of a convex-shaped pattern and its convex index.

Definition: *Time series*

A *Time Series* $X=[x_1, \cdots, x_m]$ is a continuous sequence of real values. The value of the i-th time index is denoted by $X[i] = x_i$.

Definition: *Subsequence*

A *subsequence* $S = [x_p, x_{p+1},...,x_q] = X[p:q]$ is a continuous subsequence of X starting at position p and ending at position q. We denote the length of a subsequence S by len:

$$len(S) \equiv q - p + 1$$

Definition: *Convex index*

A convex index is a 4-tuple (peak position, magnitude, left position, right position). A peak position is a time index at which the peak of a convex-shaped pattern is. A magnitude is a height of a convex-shaped pattern. A positive magnitude value means that a pattern is convex, and a negative magnitude value means that a pattern is concave. A left terminal is a time index at which a convex-shaped pattern starts. A right terminal is a time index at which a convex-shaped pattern ends.

Definition: *Convex profile*

Let X be a time series. A convex profile of X is a list of convex indexes that correspond to an output of convex pattern extraction process for input X. We denote a convex profile as CP and the i-th convex index in CP as CP(i). We denote a peak position, magnitude, left position and right position of CP(i) as CP(i).p, CP(i).m, CP(i).l and CP(i).r respectively.

Convex pattern extraction is represented as a function from a time series X to a convex profile of X. A subsequence corresponding to a convex index C(i) is represented as X[C(i).left: C(i).right] where X is a time series. We also define a magnitude function to plot the magnitude values to visualize the outline of a convex profile.

Definition: *Magnitude function*

Let X and CP be a time series and the convex profile of X respectively. Magnitude function *mf* is a function from each time index of X to a real value.

If t is a time index at which a convex index CP(i) has a value as a peak position, then *mf*[t] =CP(i).m, otherwise *mf*[t] = 0.

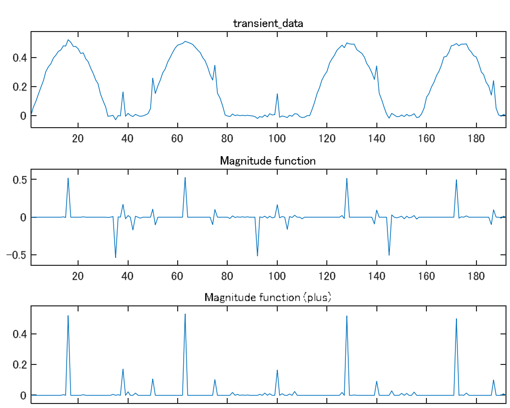

Figure 4: An example of a magnitude function

Figure 4 shows an example of a time series and its magnitude functions. Top graph is a line graph of the original time series data. The second graph is its magnitude function. We see that a convex-shaped pattern in the original data corresponds to a spike in the magnitude function. The bottom graph is the magnitude function that has only positive values. Heareafter, we use only positive magnitudes in this paper.

Table 1 shows an example of a convex profile of a time series shown in Figure 3. One line of a convex profile corresponds to one peak value in the magnitude function.

Table 1: An example of a convex profile

Peak position	**Magnitude**	**Left** termnal	**Right** terminal
16	0.52	1	32
38	0.17	35	42
50	0.11	35	51
63	0.53	35	92
75	0.10	74	81
100	0.16	92	104
128	0.52	92	145
140	0.09	139	145
172	0.50	145	190
187	0.10	186	190

3.2 Symbolic Convex Approximation

Symbolic convex approximation is a means to approximate a time series with a set of convex-shaped patterns by means of a magnitude constraint bin, which is a rule for selecting a convex index and its mapping to a symbol. A magnitude range bin is defined by the following.

Definition: *Magnitude constraint bin*

A magnitude constraint is a logical formula that consists of inequalities on magnitude. A magnitude constraint bin is a list of range constraints which are exclusive of each other.

A convex decomposition is a set of convex-shaped patterns to approximate a time series. A required magnitude level depends on the application, and we can control a magnitude constraint bin to get convex-shaped patterns that are suitable for an application. Symbolic convex approximation is a sequence of symbols used to extract a cycle that consists of regularly ordered patterns by means of a string matching technique. A convex decomposition and a symbolic convex approximation are defined in the following.

Definition: *Convex decomposition*

Let CP be a given convex profile, and let MB be a magnitude constraint bin. A convex decomposition is a set of convex patterns in CP that satisfy either one of the magnitude constraints in MB. Each convex index $C(i)$ is modified to $C'(i)$ so as not to cross another convex pattern by the following formulas:

$$C'(i).l = \max(C(i).l, \max\{C(j).r \mid j \in \{j \mid C(j).r < C(i).p\}\})$$

$$C'(i).r = \min(C(i).r, \min\{C(j).l \mid j \in \{j \mid C(j).l > C(i).p\}\})$$

Definition: *Symbolic convex approximation*
Let CP and MB be a convex profile and a magnitude constraint bin respectively. If a convex index C(i) satisfies a magnitude constraint j, symbolic convex mapping is defined to be a function from C(i) to a symbol that corresponds to j. That is, if a magnitude constraint j is different, the mapped symbol of j is different. The image of a symbolic convex mapping from a convex profile is called a symbolic convex approximation.

Figure 5 shows the convex decomposition and the symbolic convex approximation of a raw data shown in the top graph of Figure 4. The top graph is the line graph for the original data. The second graph is a convex decomposition that corresponds to a magnitude constraint "M >= 0.4", which means its magnitude is greater than or equal to 0.4. The corresponding convex shaped-patterns are labeled as "A". The third graph is a convex decomposition that corresponds to a magnitude constraint "0.075 < M and M<=0.4". The corresponding convex shaped-patterns are labeled as "B". The bottom graph is a convex decomposition that corresponds to a magnitude constraint bin {"M >= 0.4", "0.075 < M <=0.4"}. Note that the left and right terminals of the extracted convex-shaped patterns are modified by the definition of convex decompostion. The symbolic convex approximation by this decomposition is "ABBABBABAB".

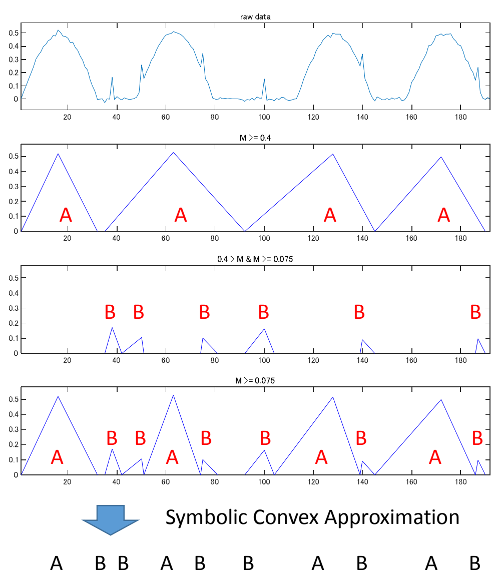

Figure 5: An example of a convex decomposition and its corresponding symbolic convex approximation

4 EXPERIMENTAL VERIFICATION

This section evaluates our method on one simulation and one real data sets.

4.1 An experiment on a simulated time series

Figure 6 shows the magnitude functions corresponding to serveral magnitude constraints for the simulated time series shown in Figure 1. The top graph is a line graph of the simulated data. The second graph is a magnitude function graph that corresponds to a magnitude constraint "M > 0", which means the magnitude value is greater than 0. The third graph is the magnitude function that corresponds to a magnitude constraint "8.5 < M". This graph shows that the convex patterns "a" and "c" in Figure 1 can be extracted by this magnitude constraint. The bottom graph is the magnitude function that corresponds to a magnitude constraint "4.5 < M and M<=8.5". This bottom graph shows that a magnitude convex pattern "b" in Figure 1 can be extracted by that magnitude constraint.

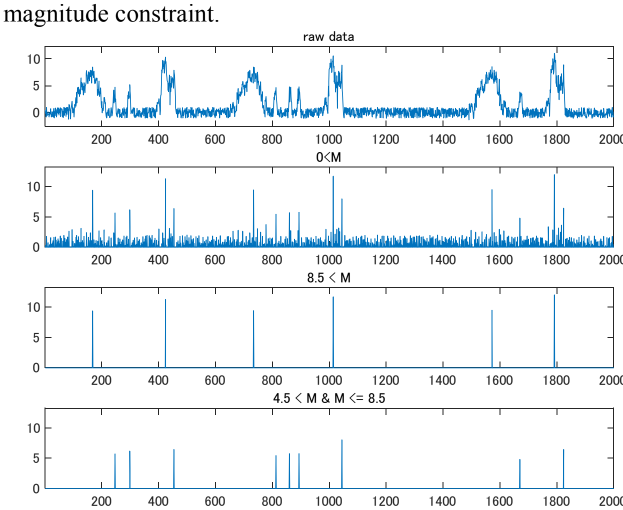

Figure 6: The magnitude functions of a simulated data set

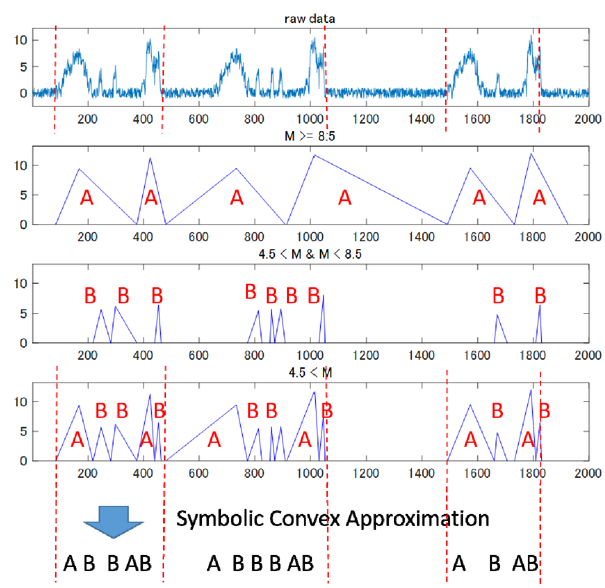

Figure 7: The convex decompositions and the symbolic convex approximation of simulated data

Figure 7 shows the convex decomposition and the symbolic approximation of the simulated data. The top graph is the line graph for the original data. The second graph is a convex decomposition that corresponds to a magnitude constraint of "M >= 8.5". The extracted convex-shaped patterns are labeled as “A”. The third graph is a convex decomposition that corresponds to a magnitude constrant “4.5 < M and M<=8.5”. The extracted convex-shaped patterns are labeled as “B”. The bottom graph is a convex decomposition that corresponds to a magnitude constraint bin of {“M >= 8.5”, “4.5 < M and M<=8.5”}.

The symbolic convex approximation by this decomposition is “ABBABABBBABABAB”. If we replace a pattern “AB” followed by the repetition of pattern “B” with “c”, we get “ABBcABBBcABc”. After this step, if we replace “A” with “a” and replace the repetition of “B” with (b+), we get “a(b+)ca(b+)ca(b+)c”. This regular exparesion is what we wanted to find. The above procedure contains an ambiguous step, because a single occurrence of “B” after “A” can match two patterns “AB” and A(B+). In the case of this example, we can disambiguate it to use the peak positions of convex shaped patterns “A” and “B”. An algorithm to aquire regular expression by using both a magnitude and a peak position can be considered in future work.

4.2 Factory Work Process

The second example involves human motion in a factory work process. Figure 8 shows an acceleration time series for a cardboard packaging process. Each cycle consists of 4 basic operations: (a) Preparing a cardboard, (b) labeling, (c) packaging and (d) carrying a cardboard. The repeated process can be segmented by discovering a motif, which is a subsequence frequently occurring in a time series. In Fig. 1, the subsequences corresponding to (a), (b), (c) and (d) are examples of motifs.

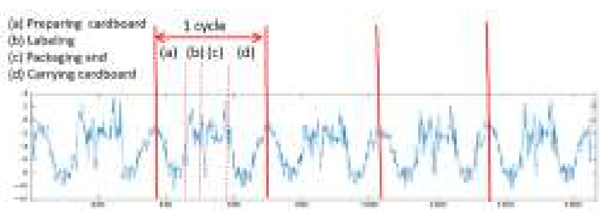

Figure 8: Time series of factory working process

The segmentation problem for this data is to extract each cycle that consists of basic actions (a), (b), (c) and (d).

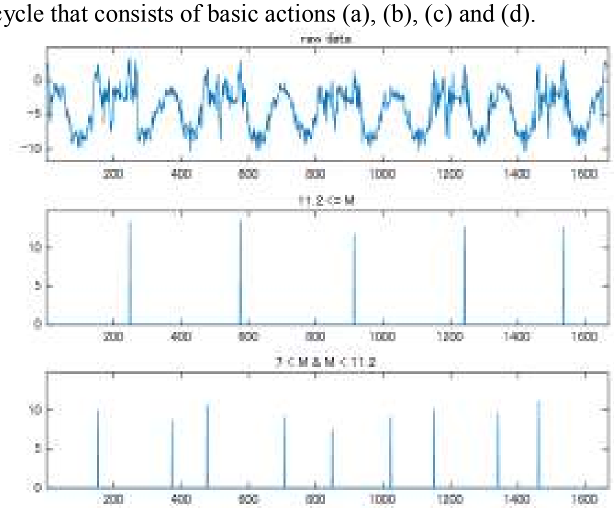

Figure 9: The magnitude function of a factory work process data set

Figure 9 shows the magnitude functions corresponding to serveral magnitude constraints for a factory work process data set shown in Figure 8. The top graph is the line graph for the raw data. The second graph is the magnitude function that corresponds to the magnitude constraint “0 < M”. The third graph is the magnitude function that corresponds to the magnitude constraint “11.2 <= M”. This graph shows that the peak of a segment “c” in Figure 8. can be extracted by this magnitude constraint. The bottom graph is the magnitude function that corresponds to a magnitude constraint “7 < M < 11.2”. This bottom graph shows that the starting point of a segment “a” and the peak of a segment “b” in Figure 8 can be extracted by that magnitude constraint.

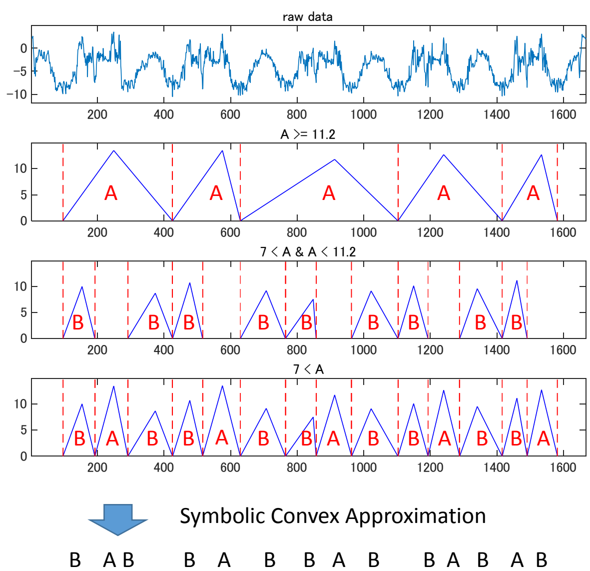

Figure 10: The convex decomposition and the symbolic convex approximation of a factory work process data set

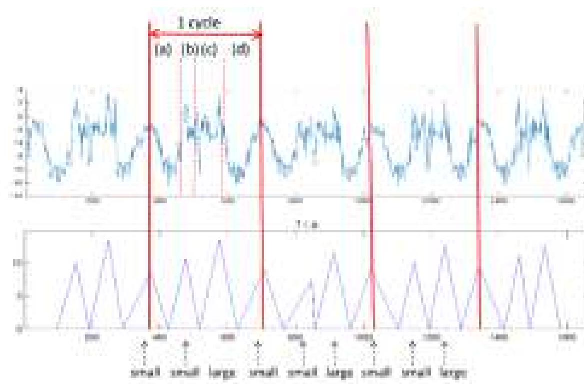

Figure 11: The relation between the segments in a factory work process data set and the extracted convex-shaped pattern

Figure 10 shows the convex decompositions and the symbolic approximation of the factory work process data. The top graph is the line graph for the original data. The second graph is the convex decomposition that corresponds to a magnitude constraint “11.2 <= M”. The extracted convex–shaped patterns are labeled as “A”. The third graph is the convex decomposition that corresponds to the magnitude constrant “7 < M <11.2”. The extracted convex-shaped patterns are labeled as “B”. The bottom graph is a convex decomposition that corresponds to the magnitude constraint bin {“11.2 <= M”, “7 < M <11.2”}.

The symbolic convex approximation by this decomposition is “BABBABBABBABAB”. This symbolic sequence does not correspond to the exact segments shown in Figure 8. However, a repeated sequence “BAB” corresponds to one cylcle, so that we can calculate the working time per one cycle. This result is useful from the point of view of our application. Figure 11 shows the relation between the segments in the factory work process and the convex-shaped pattern extracted by our algorithm. The peak of convex-shaped pattern “A” seems to correspond to the starting point of a segment “a” and the ending point of a segment “d”. How to obtain segments required by a given application by the convex-shaped pattern will also be considered in future work.

5 CONCLUSION

We defined the structural motif discovery problem and proposed a novel segmentation method that approximates the time series with a sequence of convex-shaped patterns by means of leg analysis. The experimental results show that our method has the potential to solve the structural motif discovery problem. We only evaluated our method on two simple examples. Evaluation on exhaustive data is future work. Technical future challenges include the following:

(1) Magnitude constraint selection

We manually tuned magnitude constrains depending on the experimental data. How to select an appropriate magnitude constraint is the first major challenge.

(2) Regular expression acquisition

An algorithm to aquire regular expression by using both magnitude and a peak position is also future work.

(3) Segmentation with a convex-shaped pattern

How to obtain segments required by a given application by the convex-shaped pattern will also be considered in our future work.

This work is supported by JSPS KAKENHI Grant Number 17K00161.

REFERENCES

[1] J. F. Lin and D. Kulić: "Online Segmentation of Human Motion for Automated Rehabilitation Exercise Analysis," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 22, no. 1, pp. 168-180, Jan. 2014.

[2] J. F. Lin, M. Karg and D. Kulić: "Movement Primitive Segmentation for Human Motion Modeling: A Framework for Analysis," in *IEEE Transactions on Human-Machine Systems*, vol. 46, no. 3, pp. 325-339, (2016).

[3] M. Reyes Adame, A. Al-Jawadm M. Romanovas, M. A. Hobert, W. Maetzler, K. Möller, Y. Manoli: TUG Test Instrumentation for Parkinson’s disease patients using Inertial Sensors and Dynamic Time Warping, Biomed. Eng., vol. 57, pp. 1071-1074, (2012)

[4] Masahiro Terada, Tadao Yago, Mao Inoue, Kakeru Ota, Hiroto Anzai and Makoto Imamura: An analysis Method of Baggage Lifting Motion for lower backache Prevention, IEEJ (The Institute of Electrical Engineering of Japan) 2019 Annual Conference on Electronics, Information and Systems (2019). (in submission)

[5] Tadao Yago, Mao Inoue, Junji Tsuda and Makoto Imamura, Factory Work Process Segmentation Using Acceleration Sensor, Asia Pacific Conference on Robot IoT System Development and Platform 2018 (APRIS2018), (2018).

[6] M. Imamura, J. Tsuda, D. Nikovski, and M. Tsuru : A Fast Online Algorithm for Analyzing Magnitude Fluctuation of Time Series, International Journal of Informatics Society (IJIS), Vol.10, No.2,pp. 85-96 (2018).

[7] Patel, P., Keogh, E., Lin, J. and Lonardi, S.: Mining motifs in massive time series databases. 2002 IEEE International Conference on Data Mining (ICDM), pp. 370-377 (2002)

[8] Chin-Chia Michael Yeh, Yan Zhu, Liudmila Ulanova, Nurjahan Begum, Yifei Ding, Hoang Anh Dau, Diego Furtado Silva, Abdullah Mueen, Eamonn Keogh : Matrix Profile I: All Pairs Similarity Joins for Time Series: A Unifying View that Includes Motifs, Discords and Shapelets, 2016 IEEE International Conference on Data Mining (ICDM), pp. 1317-1322 (2016).