





Duration-Aware Alignment of Process Traces



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Talk Overview

- Motivation of Research
- ☐ Duration-Aware Trace Alignment Algorithm
- ☐ Evaluation Criteria
- ☐ Case Studies

Previous Research: Expert Model

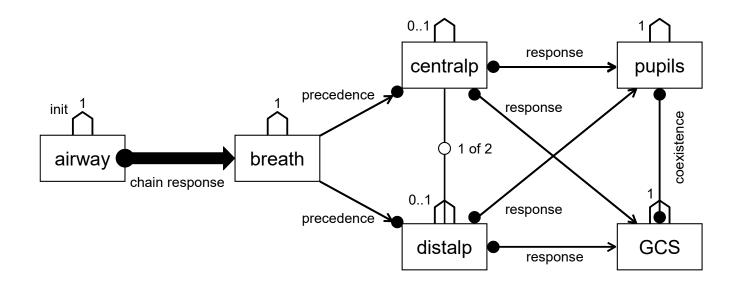


Figure: Expert-derived workflow model showing of essential activities by the bedside physician during the primary survey phase of ATLS (Advanced Trauma Life Support)

Previous Research: Trace Alignment

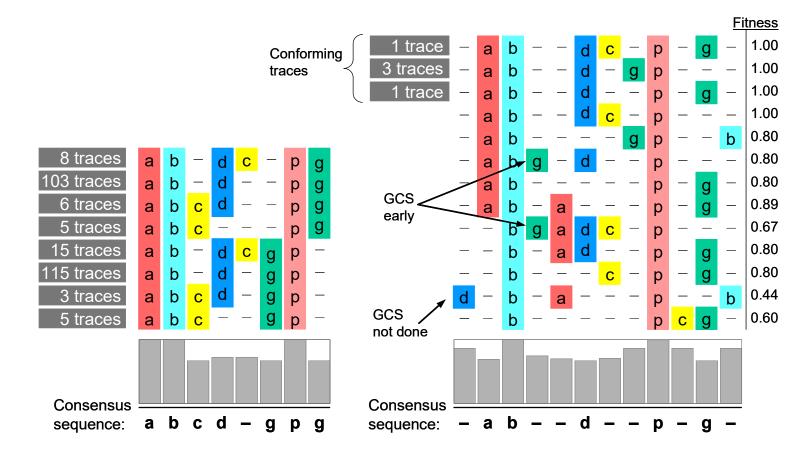


Figure: (left) Trace alignment of resuscitations conforming to the workflow model; (right) trace alignment of resuscitations in which evaluation of neurological status [GCS] was performed incorrectly.

Motivation of Duration-Aware Trace Alignment

Trace Alignment on medical processes:

- Helpful in visualizing the data
- Helpful in discovering deviations
 - similarities within a group of traces and to determine how a given trace differs from the well-established work practice
- Finding a sequential model
 - Consensus sequence can be seen as the backbone sequential model of the process

Limitation:

 Existing trace alignment approaches consider only the sequential order of activities and ignore activity duration.

Motivation

Motivation of Duration-Aware Trace Alignment

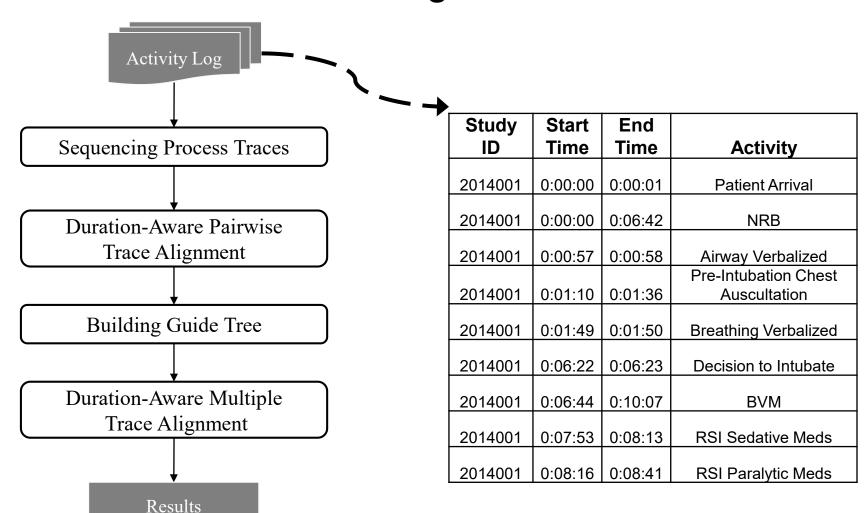
Activity duration is useful:

- Duration indicates activity similarity:
 - For example, consideration of duration helped understand that nurses routinely switch between tasks, spending less time on interrupted tasks that are later resumed
- Unusual durations indicate difficulties or atypical performance in the medical team operations

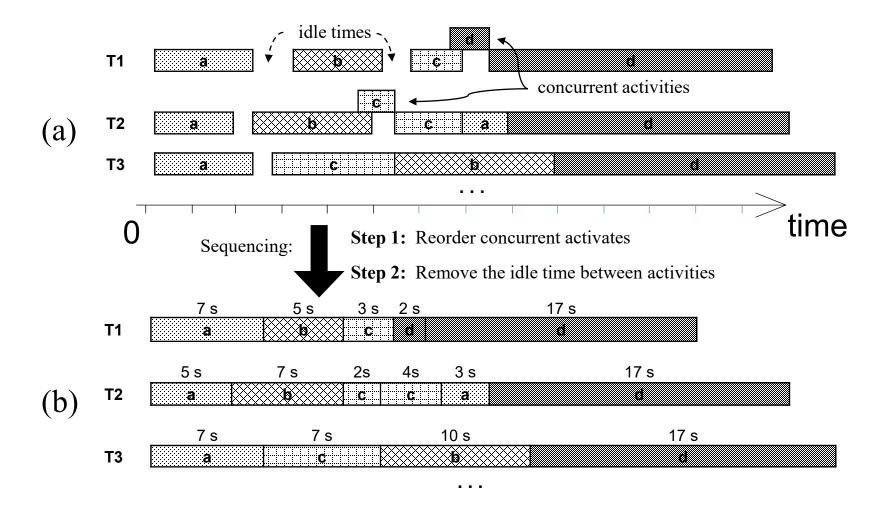
Question:

- How to include activity duration into consideration?
 - Dynamic Time Warping???

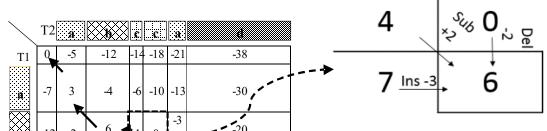
Duration-aware trace alignment flowchart

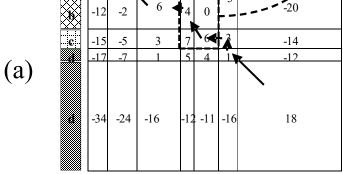


Sequencing of Process Traces



Pairwise Duration-Aware Trace Alignment





Scoring Scheme:

$$S(a,b) = 1$$
 Match
 $S(a,b) = -1$ Mismatch
 $g = -1$ Gap

$$F(i,j) = \max \begin{cases} F(i-1,j-1) + S\big(T_1(i),T_2(j)\big) * ddp\big(T_1(i),T_2(j)\big) & \text{Substitute} \\ F(i-1,j) + g * hdp(T_1(i)) & \text{Insert} \\ F(i,j-1) + g * vdp(T_2(j)) & \text{Delete} \end{cases}$$

Pairwise Duration-Aware Trace Alignment

Time Distortion Penalty Function:

$$hdp(T_{1}(i)) = \varphi(d(T_{1}(i)))$$

$$vdp(T_{2}(j)) = \varphi(d(T_{2}(j)))$$

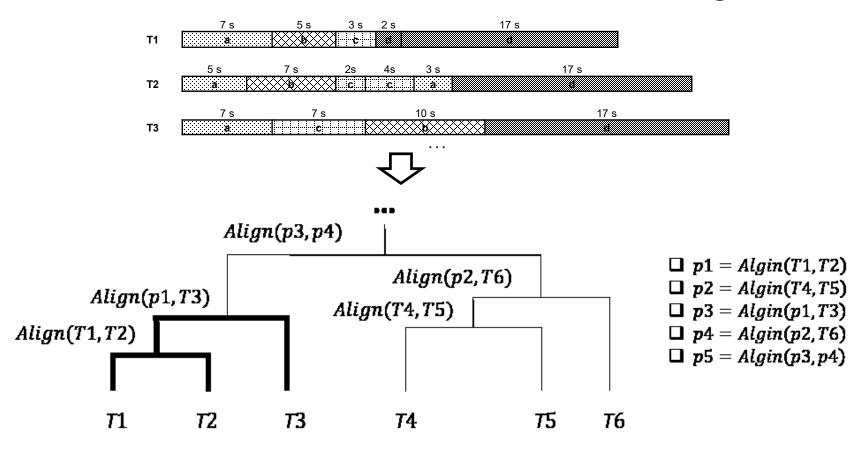
$$ddp(T_{1}(i), T_{2}(j))$$

$$= \begin{cases} Min(\varphi(d(T_{1}(i))), \varphi(d(T_{2}(j)))) - |\varphi(d(T_{1}(i))) - \varphi(d(T_{2}(j)))|, & S(T_{1}(i), T_{2}(j)) \ge 0 \\ \varphi(d(T_{1}(i))) + \varphi(d(T_{2}(j))), & S(T_{1}(i), T_{2}(j)) < 0 \end{cases}$$

Time Weighting Function:

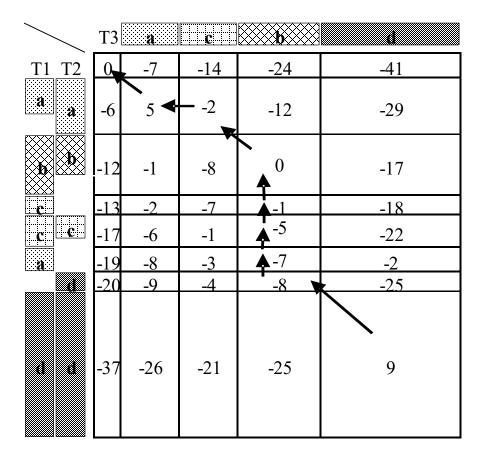
$$\begin{cases} \varphi_{Linear}\big(d(event)\big) = c * d(event) &\longleftarrow \text{ Linear weighting} \\ \varphi_{Log}\left(d(event)\right) = \log_b\big(d(event)\big) &\longleftarrow \text{ Logarithmic weighting} \end{cases}$$

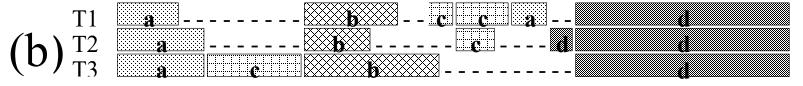
Guide Tree from Hierarchical Clustering



- ☐ Hierarchical tree grows based on Ward's method
- ☐ Similarity of process traces based on Edit Distance (a.k.a. Levenshtein Distance [11]) or Duration-Aware Edit Distance

Multiple Duration-Aware Trace Alignment





- Sum-of-pairs Score (SPS)
- Average Information Score
- Consensus Sequence (CS)
- Alignment Matrix Length
- Deviation Detection Ability

Quantitative

Qualitative

1. Sum-of-pairs Score (SPS)

$$SPS = n/N$$

n: # of correctly aligned residue (activity) pairs in the test alignment

N: total # of residue (activity) pairs in the reference alignment

Example:

Trace 1: AB -

Trace 2: A B -

Trace 3: _ B A

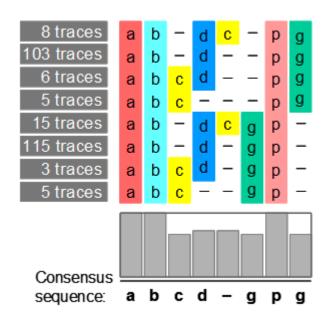
Reference Alignment

Trace 1: - A B

Trace 2: - A B

Trace 3: B A -

Test Alignment



2. Average Information Score (IS):

$$IS_i = (1 - \frac{E}{E_{max}})$$

where $E_{max} = \log_2(|\mathbb{A}| + 1)$; $E = \sum_{a \in \mathbb{A} \cup \{-\}} -p_a \log_2(p_a)$

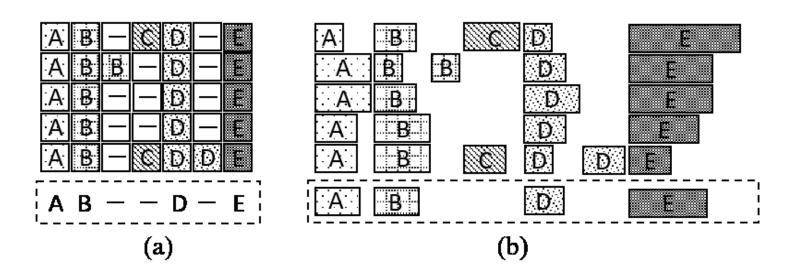
$$Avg.\,IS = \left(\sum IS_i\right)/L$$

L is alignment matrix length, i.e., # columns in alignment matrix



3. Consensus Sequence (CS):

The consensus sequence denotes a sequence of the most frequent activity found in each column of the alignment matrix.



4. Alignment Matrix Length:

Shorter matrix length is preferred. Longer alignment matrix may indicate that unnecessary gaps are included into the alignment.

Example:

Dense Matrix

Sparse Matrix

Case Study 1: Trauma Resuscitation Process



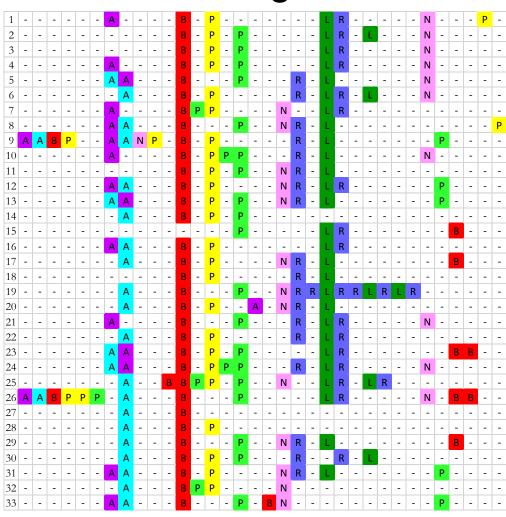
- Data Coded based on the videos in CNMC
- 33 cases with a total 244 activities of 8 different types

(Question: small data?)

Algorithm:	Duration-Aware	Duration-Aware	Context-
Metrics:	(linear)	(logarithmic)	based
Sum-of-pairs Score	0.617	0.807	0.731
Avg. Information Score	0.870	0.863	0.848
No. Non-gap Activities in CS	6	7	6
Alignment Matrix Length	49	39	36



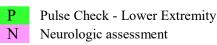
Reference Alignment



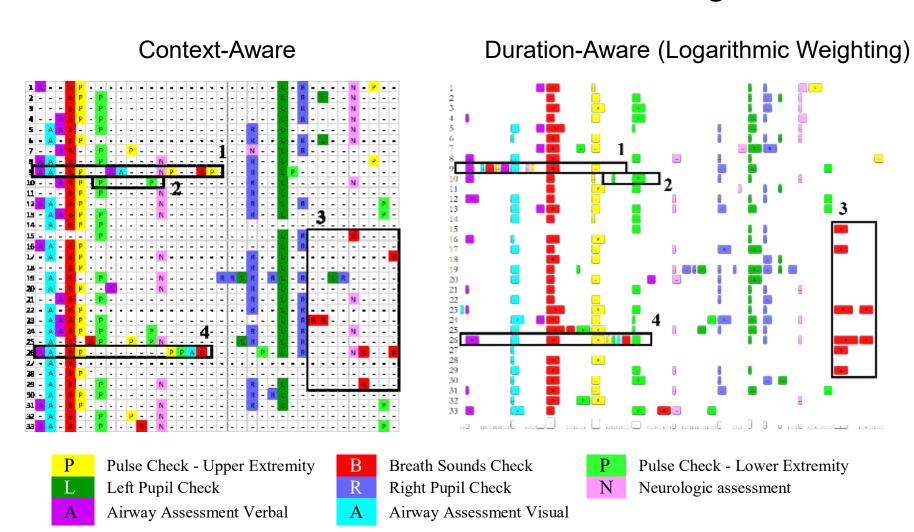
- ☐ The reference alignment functions as a ground truth.
- ☐ Created manually by medical experts.

P Pulse Check - Upper Extremity
L Left Pupil Check
A Airway Assessment Verbal

B Breath Sounds Check
R Right Pupil Check
A Airway Assessment Visual

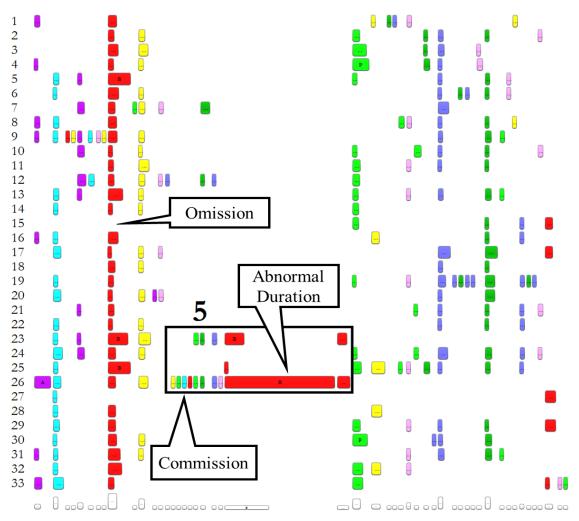


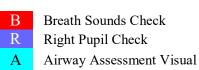
Context-Aware vs. Duration-Aware Alignment



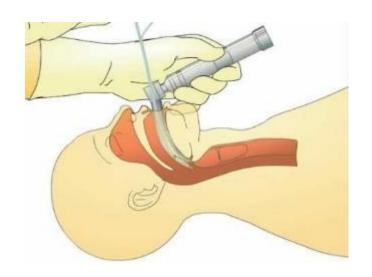


Duration-Aware (Linear Weighting)





Case Study 2: Endotracheal Intubation Process

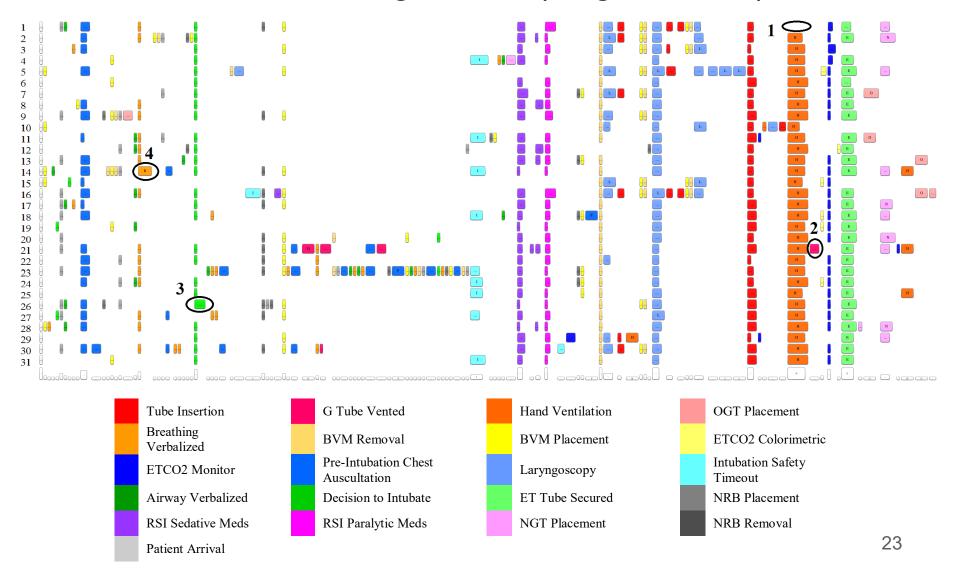


- Data Coded based on the videos in CNMC
- 31 cases with a total 602 activities of 21 different types

Algorithm:	Duration-Aware	Duration-Aware	Context-
Metrics:	(linear)	(logarithmic)	based
Sum-of-pairs Score	0.731	0.843	0.721
Avg. Information Score	0.918	0.919	0.899
No. Non-gap Activities in CS	10	12	13
Alignment Matrix Length	134	119	115



Duration-Aware Alignment (Logarithmic)





Implementation



Scalability

 $O(n^2l^2 + n^3) \rightarrow \text{Trace Clustering (i.e., Guide Tree)}$

 $O(n^2L + nL^2) \rightarrow \text{Trace Alignment}$

Where:

n: trace number

l: average trace length

L: average length of traces or profiles taken into alignment

Table. Computation Time. The notation $t \pm \delta$ denotes the computation time where t is the mean value over 20 difference runs and δ is the standard deviation

Log	No. traces	Total activities	Guide Tree (ms)	Progressive Alignment (ms)	Visualization (ms)
Intubation	31	605	15 ± 1	10 ± 1	4 ± 1
Trauma Resuscitation	33	4482	105 ± 5	242 ± 16	19 ± 2
Artificial Data	1000	52179	12493 <u>±</u> 227	12353 ± 749	591 ± 51

Conclusion

- 1) A novel trace alignment algorithm that is duration-aware
- 2) A set of criteria to quantify trace alignment algorithm performance
- Case studies showed our alignment algorithm achieved better alignment accuracy and provided more insights into deviations
- 4) Algorithm implemented into a JAVA APP

Limitations

- 1) Information lost in the "Process Trace Sequencing" step
- 2) Algorithm needs activity durations as input



Thank you question?

Have workflow data that needs visualization and analysis? Sen Yang sy358@scarletmail.rutgers.edu