

Temporal Segmentation for Capturing Snapshots of Patient Histories in Korean Clinical Narrative

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Objectives: Clinical discharge summaries provide valuable information about patients' clinical history, which is helpful for the realization of intelligent healthcare applications. The documents tend to take the form of separate segments based on temporal or topical information. If a patient's clinical history can be seen as a consecutive sequence of clinical events, then each temporal segment can be seen as a snapshot, providing a certain clinical context at a specific moment. This study aimed to demonstrate a temporal segmentation method of Korean clinical narratives for identifying textual snapshots of patient history as a proof-of-a-concept. **Methods:** Our method uses pattern-based segmentation to approximate human recognition of the temporal or topical shifts in clinical documents. We utilized rheumatic patients' discharge summaries and transformed them into sequences of constituent chunks. We built 97 single pattern functions to denote whether a certain chunk has attributes that indicate that it can be a segment boundary. We manually defined the relationships between the pattern functions to resolve multiple pattern matchings and to make a final decision. **Results:** The algorithm segmented 30 discharge summaries and processed 1,849 decision points. Three human judges were asked whether they agreed with the algorithm's prediction, and the agreement percentage on the judges' majority opinion was 89.61%. **Conclusions:** Although this method is based on manually constructed rules, our findings demonstrate that the proposed algorithm can achieve fairly good segmentation results, and it may be the basis for methodological improvement in the future.

Keywords: Natural Language Processing, Electronic Health Records, Automated Pattern Recognition, Rheumatic Diseases

Submitted: June 30, 2018

Revised: July 19, 2018

Accepted: July 23, 2018

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I. Introduction

The clinical discharge summary in the Electronic Health Record system (EHR) provides detailed descriptions of a patient's clinical events. Physicians describe a patient's disease progress in the document. Because the clinical history tends to be chronologically narrated [1], one of the prominent attributes of clinical documentation is that temporal and causality information comprise the mainstream of writing. In other words, temporal information is embedded in the clinical narrative, and causally related clinical events simultaneously deliver context.

The innate temporal aspect of clinical description makes temporal information processing valuable for utilizing the

clinical course described in clinical documents [2]. Thus, temporal processing of clinical data has been a long-standing interest [3]. Indeed, previous clinical natural language processing studies have concerned the extraction of temporal information, such as temporal relation discovery [4-8], temporal question answering systems [9], recognition of temporal patterns and visualization of patient's clinical history [10-12], as well as temporal segmentation of clinical documents [13,14].

Because of their temporality and causality, a sequence of clinical events and related descriptions can be grouped into medical episodes, and the sequence of medical episodes build the temporal structure of a text. A single episode can play the role of a single unit in temporal processing applications. For instance, the causal relationship between clinical entities, which is used in temporal processing applications, can be interpreted within an episode. This study, therefore, attempted to develop a temporal segmentation method for application to clinical narrative documents. A temporal segment is related to a single clinical episode in this study; thus, segmentation can make an intermediate form of the clinical document for clinical temporal processing. Because there is temporal discontinuity [15] between episodes in the terms of text, an important step is to recognize textual cues of the discontinuity in a free text.

A temporal segment can be interpreted as a snapshot that is literally "a piece of information that delivers readers an idea of what the situation is like at a particular time" (Longman Dictionary of Contemporary English, Pearson, 2009). Temporal segmentation divides a single clinical descriptive text into multiple pieces of narrative texts, and each segment provides temporal coherence between clinical events as shown in Figure 1. From this perspective, temporal segmentation is strongly related to discourse segmentation, as discussed by Allen [16]. A segment is defined as a stretch of clause sequences delivering coherent contents.

The most important indicators of the text structure are 'cue

phrases'. When writing is seen as a linear progression assigning linguistic symbols, authors place signals around the positions leading to a new story. Cue phrases indicate topical or temporal shifts in text structure [16,17]. Based on this idea, this study demonstrates a pattern-based segmentation algorithm for clinical narrative texts as a possible way to divide a document into multiple text snippets. Then, this algorithm can make each snippet provide a temporally or topically coherent story for restructuring of the original document. In short, our temporal segmentation algorithm aims to make textual snippets that match the results produced by human readers and that can convey clinical context.

II. Methods

This study used data from the Seoul National University Hospital EHR and was approved by the Institutional Review Board of Seoul National University Hospital (No. 1506-014-677). We obtained 200 discharge summaries of patients hospitalized in the rheumatoid and nephrology departments in 2013 and 2014. We evenly divided the data into training and testing sets, and developed the temporal segmentation algorithm from a portion of the whole training set.

We assume that most segment boundaries exist at the ends of sentences or constituency chunks; thus, it is necessary to preprocess the texts including constituency chunking and sentence boundary detection. The text dataset was manually refined by manual processes. Through constituency chunking, phrases are created from groups of words according to Korean syntactic structure. In addition, texts that convey clinical semantic information must be annotated (i.e., clinical events, temporal anchoring points). The clinical events are related to symptoms, clinical tests, diagnosis, medications, treatments, and clinical department/visit information. Temporal anchoring points are indicated by salient temporal expressions that make a group of temporally coherent textual descriptions related to same temporal information. Then,

<p>Original text 86 Due to AGC, TG c Roux-en-Y anastomosis done in SNUH. Postop FAM #3 From late '02.7 headache, visual disturbance '02.8 visited SNUH NS R/O CRP impression from Br. MRI NTR of tm. Was done</p>
<p>Snapshot #1 86 Due to AGC, TG c Roux-en-Y anastomosis done in SNUH.</p>
<p>Snapshot #2 Postop FAM #3</p>
<p>Snapshot #3 From late '02.7 headache, visual disturbance</p>
<p>Snapshot #4 '02.8 visited SNUH NS R/O CRP impression from Br. MRI NTR of tm. Was done</p>

Figure 1. Snapshots from an original clinical text. Underlines indicate temporal anchoring points.

temporal segmentation using textual cues is performed based on interactions of various segmentation rules. The segmentation logic comprises textual patterns and decision rules for identifying a temporal discontinuity in a document. The sequential steps in the whole process are shown in Figure 2.

As we focused on building the segmentation algorithm, we assumed that both the pre-processing and clinical entity annotation steps had already been developed; therefore, we used clinical texts to which preprocessing had been previously applied and in which the clinical entities had been annotated.

1. Temporal Segmentation

Our segmentation algorithm predicts the positions of segment boundaries. Offsets that present segmentation boundaries are automatically annotated within a text as the output of the algorithm. A segmentation boundary can be any position in general; however, a sentence has phrase constituency that cannot be divided semantically (e.g., a group of a verb and objects in a verb phrase). Thus, our segmentation algorithm assumes that a segmentation boundary exists between chunks in most cases to keep the segmentation outputs rational when a human reads. This process was required to utilize sentence boundary and syntactic chunking information; hence, we manually identified both the sentence and phrase constituency (chunk) boundaries in the corpus.

In previous studies, cue phrases, which are used in discourse segmentation, have been defined as linguistic expressions [16,18]. Nakhimovsky and Rapaport [15] characterized a cue phrase as a signal that allows a reader to instantly notice a temporal shift when a text is segmented. Probable candidates of cue phrases are generally considered to be pronouns [16,19], tense [16], spatial focus [20], and background knowledge [13]. According to previous observations, we found cue phrases for clinical temporal segmentation from our corpora and categorized them into several categories. A cue phrase is called a 'pattern function', and an individual function consists of input, condition, and output values as

in a general function. We found 11 categories of pattern functions using the attribute of a chunk as input and providing signals as output whether the chunk boundary should be marked to be shifted or not in the terms of temporality and topic. We reviewed training discharge summaries in sequence, and the pattern functions were collected from the 3,743 chunk boundaries. Each individual pattern function has a condition set. For instance, if we define the i^{th} individual pattern function as p_i , and a function p_i consists of one or more conditions. The element conditions of p_i are grouped by 'AND' operation, and the individual pattern is matched if and only if an arbitrary input is matched to every condition elements. The output value of each pattern function has one of the segmentation actions in the set {'shift', 'do not shift'}, and for each element, the temporal or topical focus is shifted at the end of the chunk or not, respectively. Table 1 shows categories and examples of segmentation pattern functions. In total, 97 individual pattern functions are produced in our dataset. Each pattern function is compiled on every chunk, and a pattern marks the action output at the end of a chunk when the pattern is matched to the chunk. If a chunk is not matched to any function, the chunk is marked as 'should not be shifted'.

Because multiple patterns can be matched on a decision point, we use hierarchy information of the pattern functions. We define the i^{th} condition c_i and assume two pattern functions p_j and p_k having same output value. We assume that p_j consists of c_a and c_b , and function p_k consists of c_a , c_b , and c_c . In a graphical view, the two pattern functions have a hierarchical relationship when one pattern function is entirely included in another function. By using this concept, the hierarchy relationship is checked among matched functions, and subordinate patterns are rejected in the matched results.

After the hierarchy checking, the segmentation logic is required for the confliction resolution step when two different segmentation actions conflict with each other at one decision point. From our training set, 159 priority relations are collected between conflicted nodes. For example, a single priority relationship between pattern functions p_a and p_b means

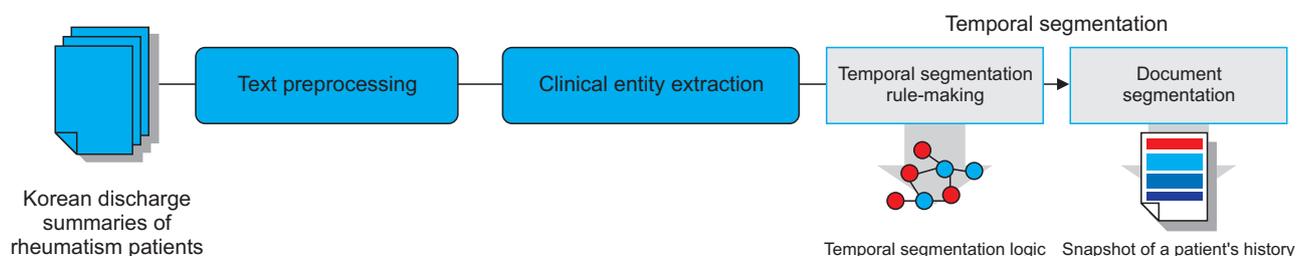


Figure 2. Process flow of temporal segmentation in Korean clinical narratives.

Table 1. Representative categories and examples of segmentation pattern functions

Category	Example (condition \rightarrow output) and description
Section	$ISA(next_chunk, section_name) \rightarrow shift$: IF next chunk is a section name THEN temporal or topical focus is shifted between the current and next chunks.
Passage	$ISA(next_chunk, dotted_line) \rightarrow shift$: IF next chunk is a dotted line (e.g., “= = =”) THEN temporal or topical focus is shifted.
Conjunction	$starts_with(next_chunk, adversative) \rightarrow shift$: IF next chunk follows current chunk with adversative conjunction THEN temporal or topical focus is shifted.
Suffix cue (similar to the proposition in English)	$ends_with(current_chunk, suffix(adversative)) \rightarrow shift$: IF the end of current chunk has functional morpheme related to adversative meaning, THEN temporal or topical focus is shifted. $ends_with(current_chunk, suffix(coordination)) \rightarrow do_not_shift$: IF the end of current chunk has functional morpheme related to coordination, THEN temporal or topical focus is continued.
Pronoun	$last_entity(current_segment) = first_entity(next_chunk) \rightarrow do_not_shift$: IF the last entity in the current segment is equal to the first entity in the next chunk, THEN temporal or topical focus is continued.
Tense	$has(current_chunk, expression(past_tense)) \wedge has(next_chunk, expression(current_tense)) \rightarrow shift$: IF the main verbs in the current chunk and the next chunk show past and current tense respectively, THEN temporal focus is shifted.
Heading	$starts_with(next_chunk, time) \rightarrow shift$: IF the next chunk starts with time, THEN temporal or topical focus is shifted. $start_with(next_chunk, arrow) \wedge has(next_chunk, time) \rightarrow shift$: IF the next chunk starts with any arrow symbol and simultaneously has any time expression, THEN temporal or topical focus is shifted.
New sentence	$ISA(next_chunk, new_sentence) \rightarrow shift$: IF the next chunk is the beginning of a sentence, THEN temporal or topical focus is shifted. $ISA(next_chunk, new_sentence) \wedge has(next_chunk, time) \rightarrow shift$: IF the next chunk is the beginning of a sentence and provides temporal information, THEN temporal or topical focus is shifted.
Knowledge	$last_entity_is(current_segment, problem) \wedge first_entity_is(next_chunk, action) \rightarrow do_not_shift$: IF the last entity in current segment is related to any problem types (symptom, disease) and the first entity in next chunk is related to any action types (treatment, medication), THEN temporal or topical focus is continued.
Inference	$discontinuity_of_visit(current_chunk, next_chunk) \rightarrow shift$: IF the current chunk provides any information about patient’s discharging from the hospital, and the next chunk provides any information about patient’s admission, THEN infer that temporal or topical focus is shifted.
Subtopic	$within(next_chunk, parentheses) \wedge has(next_chunk, time) \rightarrow do_not_shift$: IF the next chunk is within in a parentheses pair and has not any temporal information, THEN temporal or topical focus is continued.

The condition is described in a function form. The expressions ‘current’ and ‘next’ are relative between two consecutive chunks.

that one of them suppresses the other function's output when two functions are simultaneously matched to the same decision point. To avoid sparse data problem, we expand the priority annotation by using a graphical perspective. If pattern p_a suppresses p_b , and p_c is a pattern similar to p_a , then the annotation p_b also suppresses p_c . Finally, the priority checking step suppresses low priority functions, and the logic's final segmentation decision accepts dominated segmentation action. If the final segmentation actions still conflict, then the logic marks the decision point as 'should not shift'. Two or more temporal anchoring points may exist in the segment, although the segmentation logic infers whether a decision point should be segmented; thus, a heuristic post-processing step is applied to resolve the segments. For example, the post-processing first checks whether the temporal anchoring points in the current segment indicate the same time point or not, and it performs extra segmentation within the segment by using some heuristic rules. Figure 3 graphically illustrates the detailed segmentation process.

2. Algorithm Development Process

The patterns and the priority relations were incrementally collected from the training data. We observed segmentation patterns for each document, and the pattern function collection was updated when new pattern functions appeared. As a consequence, half of the pattern functions were discovered from the first 5 documents, and the frequency of the newly discovered patterns from each new document tended to be very low after the 5 documents. In other words, collected segmentation patterns in the previous documents can properly segment most of the following documents. According to this tendency, the pattern collection was iterated for exploring 50 documents, and the patterns were arranged by testing the patterns on another development set of 15 documents.

3. Human Evaluation Process

The human judge group consisted of two medical doctors and one biomedical researcher. Also, they were native Korean speakers who could use English fluently. The human judges were provided a Web-based interface for the temporal segmentation evaluation. The interface presented the algorithm's segmentation outputs. Through the interface, the judges were asked whether they agreed or disagreed with the algorithm's single predictions at each segmentation boundary where the algorithm predicted a boundary. In addition, they provided corrections at each segment if they did not agree with the algorithm's prediction. The corrections were used for reference in the quantitative evaluation.

III. Results

The prediction results produced by the temporal segmentation algorithm were assessed in comparison to multiple human experts' agreement on the segmentation output. During the evaluation, three human judges were independently asked whether they agreed with each segmentation output and to make corrections of the segmentation boundaries. Using the individual experts' corrections as reference segmentations, we evaluated our model in terms of precision, recall, and F1 for each segmentation boundary. The test dataset for temporal segmentation comprised 1,243 clinical sentences and 1,849 chunks in 30 clinical documents (average number of sentences per document, 41.4). We noted that we only used a certain portion out of the whole test set to make the human experts' revision process tolerable with a proper number of documents to evaluate.

The segmentation algorithm scanned the given 1,849 chunks and made 895 individual temporal segments in the test set. The human judges marked their opinion whether they agreed or disagreed at each decision position and made

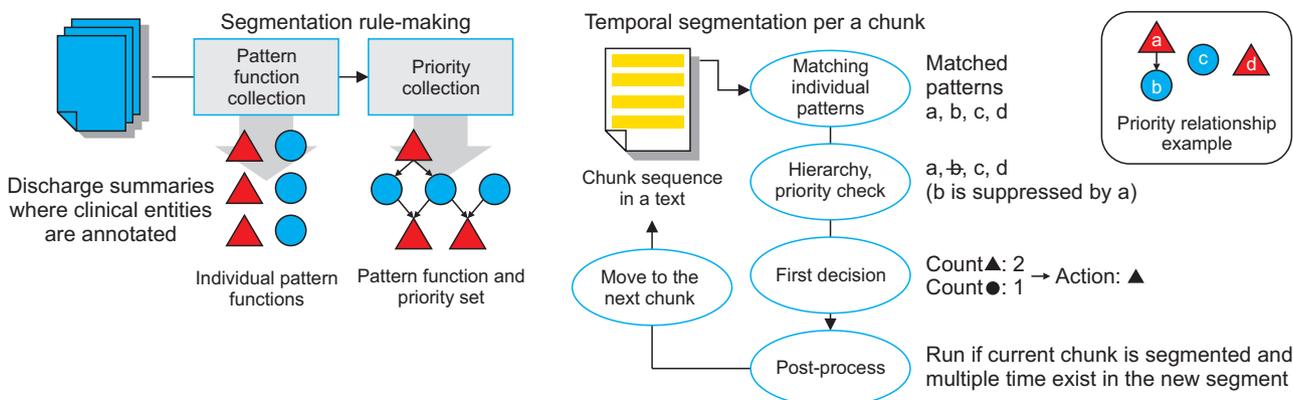


Figure 3. Graphic illustration of the temporal segmentation steps.

corrections if necessary. The number of times the human judges agreed with the algorithm results out of the 895 temporal segments were 822, 759, and 791 per judge, respectively. The majority opinion at each decision point was used as the final decision. That is, if two or all judges agreed at a certain point, then the final decision was marked as 'agreed'; otherwise, it was marked as 'disagreed'. The majority opinion agreed with the algorithm's results for 802 decision points out of the 895 points (89.61%). Inter-rater agreement was calculated according to [21,22]. The percentage agreement is used to calculate the inter-rater agreement among multiple judges; it is the ratio of the number of agreements with the major opinion over the number of possible agreements with the major opinion. In our evaluation, the number of possible agreements was 2,685 (= 895 × 3), and the human judges agreed with the majority opinion 2,501 times. Consequently, the agreement percentage was 93.1%. As previously stated, each judge provided corrections of the algorithm's outputs during the evaluation, and they made 863, 910, and 793 segments, respectively. Table 2 summarizes the qualitative evaluation results.

By using the judges' segmentation correction as human segmentation references independently, the algorithm's outputs were quantitatively measured in terms of precision, recall, and F1-score. For measuring segmentation outputs, precision is the number of correct boundary predictions over the number of the algorithm's predictions; recall is the number of correct predictions over the number of segmentation boundaries in the judge's reference. F1-score is the harmonic mean of the precision and recall. Table 3 presents the evaluation results. The first row shows the averaged value for the references made by the three independent human judges. The other rows show the quantitative evaluation results for the references made by individual judges.

IV. Discussion

The reason we used the qualitative evaluation as the first

measurement was that judges' temporal granularity inconsistently varies depending on the human cognition if explicit temporal information is absent. When we asked the judges to make segmentation boundary corrections, their corrections tended to differ from each other. For instance, judge #2 preferred to make fine-grained segments, resulting in 910 segments, whereas judge #3 preferred to make relatively coarse-grained segments, resulting in 793 segments. This means multiple forms of snapshots are allowed. We were concerned that the segmentation boundaries predicted by the algorithm with which humans may agree could be identified as incorrect if the reference decision boundary was pre-defined and fixed before testing of the algorithm. Thus, on our evaluation the algorithm's predictions were given to the human judges, and the judges determined whether or not they agreed. In addition, building a single consented segmentation reference was challenging. A general method for creating a single reference annotation is to use majority opinion; however, when the judges' corrections were merged, we observed that marginal errors could make the textual snippet awkward. For this reason, each individual's corrections were tested independently in the quantitative evaluation.

Document or discourse segmentation algorithms are generally evaluated by P_k [23] and WindowDiff [24], allowing near-misses; however, in our temporal segmentation exact segmentation boundary prediction is preferred because human readers recognize linguistic awkwardness if subtle segmentation boundary errors occur. Thus, our quantitative evaluation for the segmentation algorithm uses measurements that only accept exactly correct boundary predictions.

Beyond simple lexical cues, segmentation signals from domain knowledge were exploited; however, our rules could not cover signals requiring more intelligent sense, such as a sense of clinical location. Some location information without temporal information can signal readers that a temporal shift has occurred. For instance, 'admission' and 'follow-up' events may conflict in the terms of temporal information. Another example concerns distinguishing clinical events during a pa-

Table 2. Summary of the qualitative evaluation result

Category	n (%)
Number of segments system expected	895
Number of agreements per each judge	822, 759, 791
Number of agreements of majority opinions	802 (89.61)
Percentage agreement (%)	93.1
Number of segments after correction per each judge	863, 910, 793

Table 3. Quantitative results of temporal segmentation

Judge	Number of segment	Precision	Recall	F1-score
#1	863	0.859	0.891	0.875
#2	910	0.844	0.830	0.837
#3	793	0.819	0.924	0.868
Total (average)	-	0.841	0.882	0.860

tient's hospitalization from those during an outpatient visit following hospitalization. For instance, two events, a routine treatment with a high-dose immunosuppressant during a patient's hospitalization and the next routine during an outpatient visit should be distinguished even if the explicit temporal information is absent. Although some human judges recognize the temporal shift between two events, it is difficult to translate into rules.

Our motivation was to build a method to providing intermediate forms for clinical temporal processing applications utilizing temporal snapshots. If a temporal normalization method [25] is applied to temporal segments to chronologically arrange the snapshots, the temporal structure information would be helpful in creating a timeline visualization of a patient's history and mining semantic relationships, such as the temporal order of clinical events and causal relationships [10,26-29]. However, there are some points that should be considered to improve our knowledge further. First, summarizing an idea into a kind of linguistic presentation seems too complex to be abstracted without any information loss. As well, clinical records contain a significant number of arbitrary tabular layouts of words or nested structures of temporal information in terms of syntax. Our method is a linear progression of a text; thus, the method seems to have difficulty, especially for the arbitrary layout structure beyond the linear structure. These issues are challenges that must be addressed for the building of further temporal processing applications.

This paper presented a temporal segmentation method for capturing snapshots of patient histories in Korean clinical discharge summaries. Each segment provides a temporally or topically coherent story for restructuring the original document. Human judges were asked whether they agreed with the temporal segmentation results, and the percentage of agreement with the majority opinion was 89.61%. Temporal segmentation of clinical free texts has not been fully explored in the medical informatics domain, and only a few related studies have been previously conducted [13,30]. Although this study has the limitation that the algorithm relied on human intervention for its construction, this study provided an important opportunity to advance the understanding of clinical document segmentation regarding the temporal coherence of clinical events. This study demonstrated a trial implementing the temporal processing of clinical texts based on intuitive segmentation features. We plan to improve our method by adding machine learning approaches that minimize human intervention in this process in the future. This would lead to more generalizable temporal segmentation

methods for clinical narrative documents.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

Acknowledgments

This work was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (No. NRF-2015R1D1A1A01058075), and also supported by a grant of the Korea Health Technology R&D Project through the Korea Health Industry Development Institute, funded by the Ministry of Health & Welfare, Republic of Korea (No. HI14C1277).

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