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Semantic Waveform Measurement Method of Kansei Transition for Time-series Media Contents

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Abstract

In this paper, we present a semantic waveform measurement method of Kansei transition for time-series media contents. Kansei Transition is changes in user's sensitivity evoked by time-series changes in media content. It is important to apply the time-series change of media content to Kansei information processing as Kansei transition. In our method, we represent Kansei transition by time-series change of media content as waveforms. In addition, we realize semantic waveform similarity measurement by comparison with Kansei transitions represented by waveforms applying a signal processing technique. The semantic similarity measurement enables to measure similarity between each waveform which is extracted from media contents on time-series. In our method, it is possible to realize media content retrieval and recommendation systems corresponding to the time-series Kansei transition of media content. Our method consists of two modules: Kansei transition extraction module and semantic waveform similarity measurement module. The Kansei transition extraction module extracts time-series Kansei magnitude from the features of time-series media contents as Kansei transition. The semantic waveform similarity measurement module measures similarities between each waveform represented as Kansei transition. Our method enables to calculate the similarity of media content based on time-series changes in Kansei. We can apply our method to new media content retrieval depending on time-series change in media content Kansei.

Keywords: Kansei transition, Semantic waveform measurement, Time-series media contents, Media transition retrieval

1 Introduction

Recently, it has been distributed various types of digital media content on the internet. In this environment, it is necessary to retrieve appropriate media content corresponding to the user's intentions. Especially, it is important to realize a retrieval system for media content based on human Kansei. The Kansei means several meanings of sensitive recognition, such as "impression," "human senses," "feelings," and "sensitivity." By applying Kansei to the system, we obtain the chance to acquire appropriate media contents.

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Generally, the Kansei changes every moment according to changes of media contents. It is important to extract Kansei transition according to the time-series change of the media content. Kansei Transition is changes in user's sensitivity evoked by time-series changes in media content. The purpose is to draw out the dynamism of media content. For example, the storyline is important in a novel. There are works that differ in their manner of expression but have similar storylines. We can infer the author's background from this similarity of storyline. When evaluating movies and music, it is important not only to examine the overall impression of the work, but also the impression evoked by each scene. Media content expresses Kansei characteristics not only by the features of the media content itself, but also by the changes to features in a relative time series.

We focus on Kansei transition which is time-series Kansei variation according to time-series changes in media contents. We represent the dynamism of media content by extracted Kansei transition. Furthermore, when we realize similarity measurement method between each Kansei transition extracted from each media content, we can realize retrieval system corresponding to the dynamism of the media content. That is, it is important to realize similarity measurement based on Kansei transition corresponding to the change of features in media content.

In this paper, we present a semantic waveform measurement method of Kansei transition for time-series media contents. It is important to apply the time-series change of media content to Kansei information processing as Kansei transition. In our method, we represent Kansei transition by time-series change of media content as waveforms. In addition, we realize semantic waveform similarity measurement by comparison with Kansei transitions represented by waveforms applying a signal processing technique. The semantic similarity measurement enables to measure similarity between each waveform which is extracted from media contents on time-series. In our method, it is possible to realize media content retrieval and recommendation systems corresponding to the time-series Kansei transition of media content.

Kitagawa & Kiyoki [1] have proposed a media-lexicon transformation operator. This is the one of the frameworks for extracting metadata which represents impressions of media content as weighted words. We have also applied this to various media contents such as music [2] and images[3]. Extending the media-lexicon transformation operator [1] to a time series makes it possible to express Kansei transition.

Our method consists of two modules: Kansei transition extraction module and semantic waveform similarity measurement module. The Kansei transition extraction module extracts time-series Kansei magnitude from the features of time-series media contents as Kansei transition. The semantic waveform similarity measurement module measures similarities between each waveform represented as Kansei transition. Our method enables to calculate the similarity of media content based on time-series changes in Kansei. We can apply our method to new media content retrieval depending on time-series change in media content Kansei.

The main features of this paper are as follows.

- We propose a semantic waveform measurement method of Kansei transition for time-series media contents.

- We realize two modules: a Kansei transition extraction module, by extending the Media-lexicon transformation operator to time series, and a semantic waveform similarity measurement module, by applying a signal processing technique.
- We represent an example of the application of semantic waveform measurement method to text data such as a novel.

This paper is organized as follows. In section 2, we present two related works of our method, an overview of the media-lexicon transformation operator [1] for transformation from media content to Kansei, and one of the similarity computation methods for waveforms, dynamic time warping(DTW)[4][5][6]. In section 3, we present our proposed semantic waveform measurement method of Kansei transition for time-series media contents. In section 4, we show some preliminary experiments. Finally, in section 5, we summarize this paper.

2 Related Works

By extracting Kansei transition, it is important to realize transformation from media content to Kansei. Media-lexicon transformation operators [1] extract metadata which represents impressions of media content as weighted words as Kansei. In section II-A, we present an overview of the Media-lexicon transformation operator. It is important to realize waveform similarity computation by computing time-series Kansei transition. In section II-B, we present one of the similarity computation methods for waveforms, dynamic time warping (DTW)[4][5][6].

2.1 Media-lexicon Transformation Operator

Media-lexicon transformation operator ML can extract metadata which represents impressions of media content, such as music and images, as weighted words. ML is an operator which has relationships between features of media content and some group of word sets provided by research done by an expert in a specific disciplinary area. The operator ML is defined as follows.

$$ML(Md): Md \mapsto Ws.$$

where, *Md* is an expression of media content and *Ws* is a specific set of words usually with weights. Media content *Md* is a specific expression of the media content. Word set *Ws* is selected by an expert to express the impression of the specific media content.

Figure 1 shows one of the realization methods for the media-lexicon transformation operator. The realization operator consists of transformation matrix T, media content vector $\boldsymbol{x}$, and word vector y. Transformation matrix T represents a relationship between features $\{x_1, x_2, \ldots, x_n\}$ of media content and words selected by an expert $\{w_1, w_2, \ldots, w_m\}$. The matrix is usually provided by the expert's research. For example, in the case of music media content [1][2], we can apply Hevner's research [7] to the matrix. In the case of image media content [3], we can apply a color image scale [8] to the matrix. In cases in which there is no expert research, we have also proposed a creation method for transformation matrix T by utilizing a favorability rating questionnaire survey as training data [9].

Media content vector x represents features of media content. For example, in the case of image media content[3], the vector consists of color variations. Word vector $\boldsymbol{y}$ is composed of weights corresponding to each word. The vector is derived by applying media content vector $\boldsymbol{x}$ to transformation matrix T.

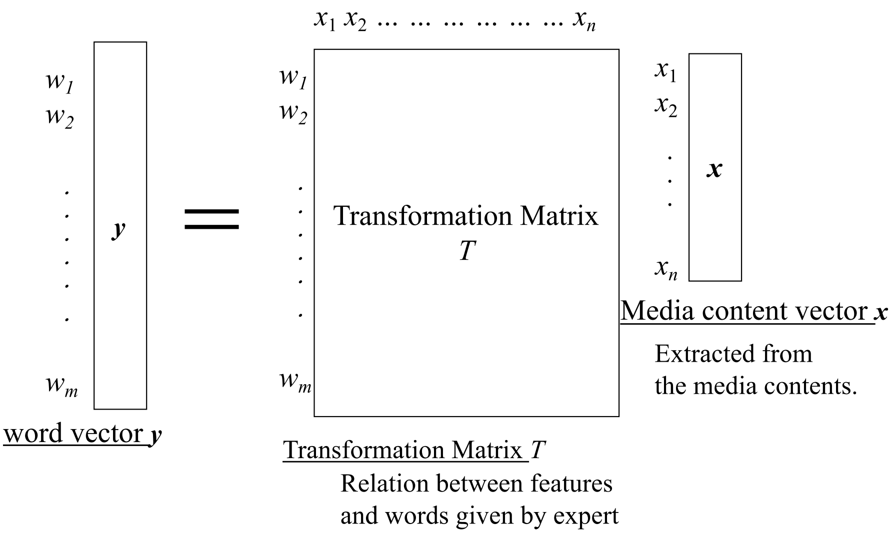

Figure 1: Realization of media-lexicon transformation operator. This operator consists of a transformation matrix T, a media content vector $\boldsymbol{x}$, and word vector $\boldsymbol{y}$.

Figure 2 shows an actual data flow of media-lexicon transformation operator. The n-dimensional vector consisting of n features is generated from the media content. In the media-lexicon transformation operator, the m-dimensional vector consisting of weights for m words is generated by applying the n-dimensional vector.

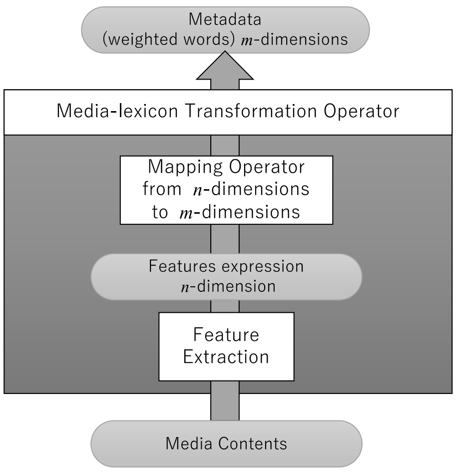

Figure 2: Data flow of media-lexicon transformation operator. Features that represent the characteristic of the media content are extracted from media content itself. The m-dimensional metadata is derived by using n-dimensional features.

This media-lexicon transformation operator does not consider the time-series changes of media content. Time-series changes in media content change its impression. In our proposed method, we extend the media-lexicon transformation operator to time series so that it is possible to represent Kansei transition.

2.2 Dynamic Time Warping (DTW)

DTW (Dynamic Time Warping) [4][5][6] is a pattern-matching technique used for one of the signal processing techniques, such as voice recognition, and so on. DTW can robustly determine the distance between two sets of time-series data with different lengths, such as waveforms with different frequencies. DTW finds the path where the two sets of time-series data are the shortest after calculating the distance between each point of the two sets of time-series data by brute force.

Fig. 3 shows the difference between Euclidean matching and dynamic time warping matching. DTW matching minimizes cumulative distance measurement consisting of local distances between aligned samples.

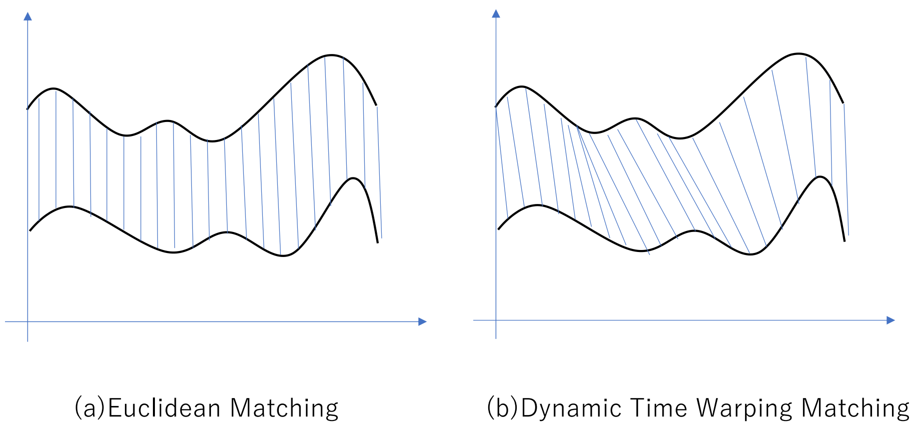

Figure 3: Different matching of two similar time series. (a) is Euclidean matching. (b) is dynamic time warping matching. The DTW matching minimizes cumulative distance measurement consisting of local distances between aligned samples.

The DTW distance $d(P,Q)$ of two different sets of time-series data $P = \left(p_1, p_2, \ldots, p_{n_p}\right)$, $Q = \left(q_1, q_2, \ldots, q_{n_q}\right)$ is defined as follows:

$$d(P,Q) = f\left(n_P, n_Q\right).$$

Here, $f(i,j)$ is defined recursively as follows:

$$f(i,j) = \left\|p_i - q_j\right\| + \min\left(f(i,j-1), f(i-1,j), f(i-1,j-1)\right)$$

$$f(0,0) = 0,$$

$$f(i,0) = f(0,j) = \infty.$$

However, since many identical terms appear during recursion, the amount of computation can be reduced by performing the actual computation from the bottom up.

Using the DTW distance makes it possible to determine short distances when each waveform shape is similar even if the time lengths of the two sets of time-series data are different. We apply DTW distance to similarity measurement of Kansei transition for time-series media content. Using the DTW distance makes it possible to search for media content with similar time-series changes in Kansei.

3 Semantic Waveform Measurement Method of Kansei Transition

In this section, we present our new method — semantic waveform measurement method of Kansei transition for time series change of media contents. In our method, we represent Kansei transition by time-series change of media contents as waveform.

We realize new time-series semantic waveform measurement by comparison with Kansei transitions represented by waveforms applying a signal processing technique. We can apply this measurement to DTW distance. Using this measurement makes it possible to realize media content retrieval and recommendation systems corresponding to the time-series Kansei transition of media content.

In section 3.1, we present an overview of our semantic waveform measurement method of Kansei transition for time-series media content. Our method consists of two modules: Kansei transition extraction module and semantic waveform similarity measurement module. In section 3.2, we represent a Kansei transition extraction module. This module is constructed by extending the media-lexicon transformation operator to a time series so that it is possible to represent Kansei transition. In section 3.3, we present a semantic waveform similarity measurement module applying DTW distance. In section 3.4, we present an example of the application of our method to text data such as a novel.

3.1 Overview of Semantic Waveform Measurement Method

Figure 4 shows an overview of our semantic waveform measurement method of Kansei transition for time-series media content. In our method, we represent Kansei transition by time-series change of media content as waveforms. Representing the Kansei transition as waveforms means having the Kansei magnitude in the time series. Expressing the Kansei transition as waveforms makes it possible to calculate the evaluation of the Kansei transition using signal processing techniques. Using signal processing techniques makes it possible to compute similarities of time-series data. Our method can realize a data management system based on Kansei changes evoked from time-series media content. To realize the data management system based on time-series Kansei changes, it is necessary to realize an extraction function for time-series Kansei metadata from media content and design new distances for similarity of Kansei metadata extracted as waveforms. Our method consists of two modules: Kansei transition extraction module and semantic waveform similarity measurement module.

The Kansei transition extraction module extracts time-series changes in Kansei. This module extracts features in each time. Next, these features are transformed to Kansei metadata. The transposed Kansei metadata is represented in waveforms. The change at each time indicated by these waveforms is regarded as a Kansei transition.

The semantic waveform similarity measurement module discovers other media contents by computing waveform measurements as similarities of Kansei transition. Expressing the Kansei transition as waveforms makes it possible to calculate the evaluation of the Kansei transition using signal processing techniques. DTW distance is positioned as one of the signal processing techniques to evaluate Kansei transition.

Implementing two modules makes it possible to perform a similar search for media content that represent Kansei transitions as waveforms. In addition, it is possible to visualize time-series variance by time-series change of media content. Measuring the distance of the Kansei transition in time series extracted from each media content makes it possible to derive a similarity corresponding to the dynamism of the media content.

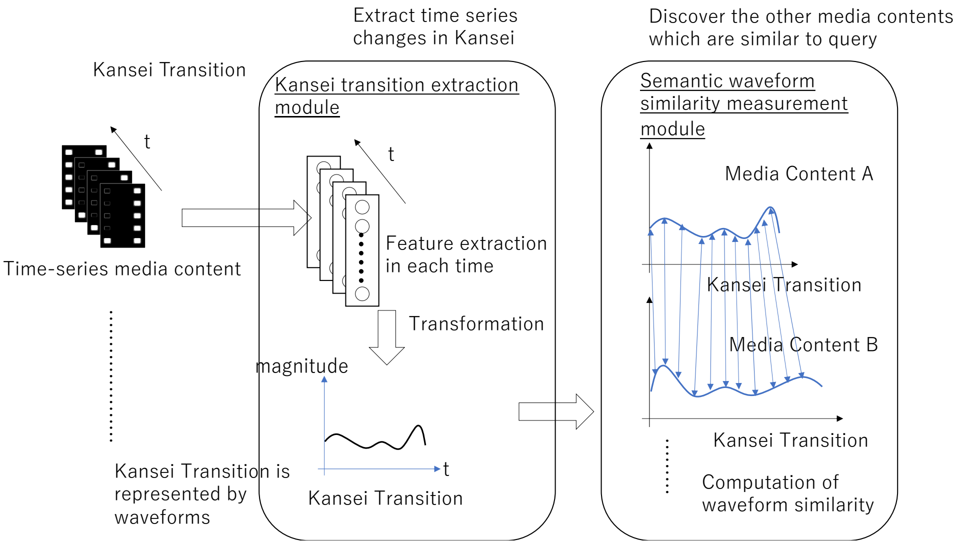

Figure 4: An overview of our waveform method of Kansei transition for time-series media content. Our method consists of two modules: Kansei transition extraction module and semantic waveform similarity measurement module. The Kansei transition extraction module extracts time-series changes in Kansei. The semantic waveform similarity measurement module discovers other media content by computing waveform similarities as similarities of Kansei transition.

3.2 Kansei Transition Extraction Module

Figure 5 shows the actual data flow of a Kansei transition extraction module. The h Kansei transition extraction module is realized by extending the media-lexicon transformation operator[1]. It divides media content into specified window sizes and extracts n-dimensional features by each time. It transforms n-dimensional features into m-dimensional words in each time. That is, it transforms from a $n \times T$ matrix to a $m \times T$ matrix.

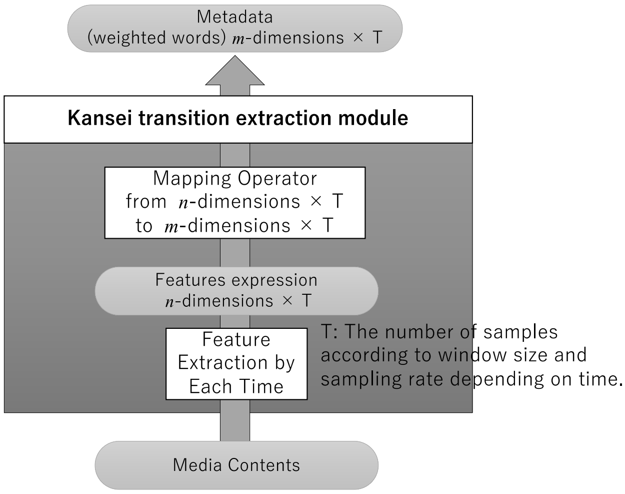

Figure 5: Data flow of a Kansei transition extraction module. It divides media content into a specified window size and extracts n-dimensional features by each time. It transforms n-dimensional features into m-dimensional words in each time. That is, it transforms a $n \times T$ matrix to a $m \times T$ matrix.

Figure 6 shows one of the realization methods for the Kansei transition extraction module. This realization module consists of a transformation matrix, a media content matrix, and a word matrix.

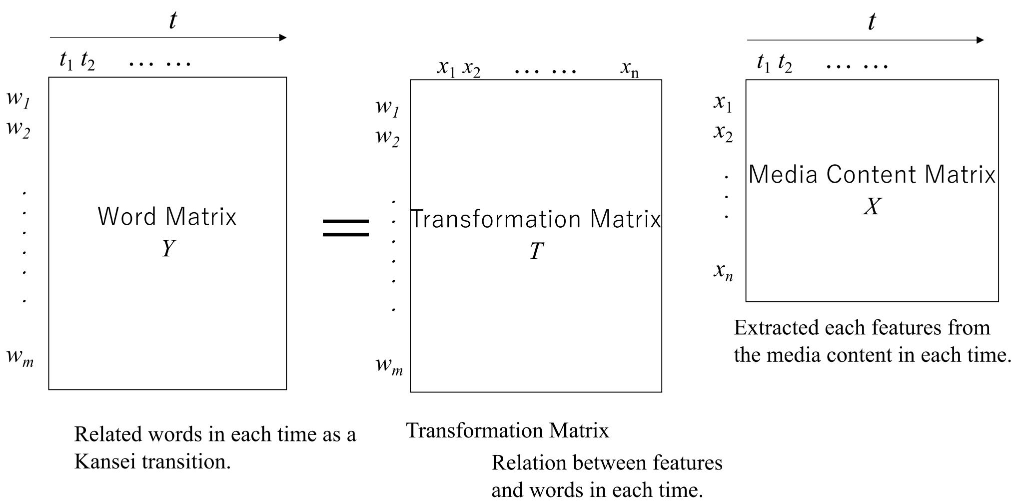

Figure 6: Realization of a Kansei transition extraction module. This consists of a transformation matrix, a media content matrix, and a word vector matrix. It transforms a n×T matrix to a m×T matrix.

The transformation matrix T represents the relationship between features $\{x_1, x_2, \dots, x_n\}$ of media content and words selected by an expert $\{w_1, w_2, \dots, w_m\}$. The transformation matrix T represents the relationship between features of media content and words.

Media content matrix X represents features of media content in each time. It means that the module divides the media content according to the window size and extracts the features for each time. That is, the module extracts the media content vectors $\boldsymbol{x}$ for each time and generates the media content matrix by composing the vectors for each time.

Word matrix Y represents weights corresponding to each word in each time. Each word of word matrix Y is regarded as a Kansei element. That is, word matrix Y represents waveforms as Kansei transition as each Kansei element's magnitude for each time. Figure 7 shows an example of representation for word matrix Y and waveforms as Kansei transition. For example, suppose that m is 2, w_1 is happiness, and w_2 is sadness in the word matrix. Word matrix Y represents each magnitude of happiness and sadness for each time in certain media content. When the value of word matrix Y is plotted on the time axis, waveforms are visualized for each word (Kansei element).

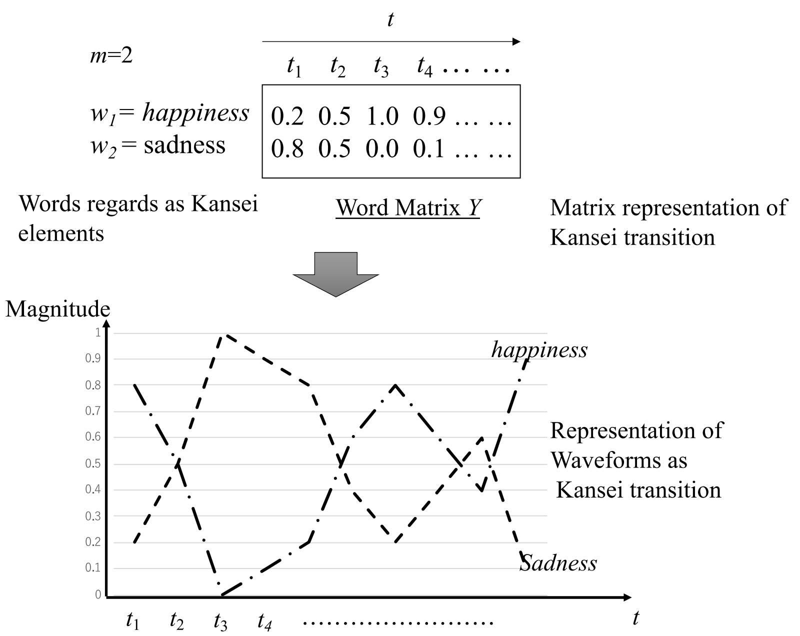

Figure 7: Word matrix Y to waveforms as Kansei transition. For example, suppose that m is 2, w_1 is happiness, and w_2 is sadness in the word matrix. The word matrix Y represents each magnitude of happiness and sadness for each time in certain media content. When the value of word matrix Y is plotted on the time axis, waveforms are visualized for each word (Kansei element).

The Kansei transition extraction module consists of four steps.

(1) Dividing media content according to a specified window size

It divides the media content at regular intervals according to a specific window size to obtain time-series characteristics from the media content.

(2) Extracting features from each part of divided media content

It extracts features from each part of the media content divided in (1) as a characteristic of the media content for each time. These extracted T features are represented as the $n \times T$ media content matrix X in Figure 5.

(3) Transforming from features to Kansei elements

It converts the Kansei elements corresponding to the features extracted in (2) as words. This transformation is realized by applying a media content matrix to the transformation matrix. In Figures 5, we can generate the word matrix Y.

(4) Representing waveforms as Kansei transition

It represents multiple waveforms as Kansei transition. Word matrix Y represents waveforms as Kansei transition as each Kansei element's magnitude for each time. When the value of word matrix Y is plotted on the time axis, waveforms are visualized for each Kansei element. We define the multiple waveforms as Kansei transition.

3.3 Semantic Waveform Similarity Measurement Module

It is possible to show the relationship between each media content based on time-series development by calculating the similarity between the Kansei transitions represented as waveforms. We call a semantic waveform similarity measurement. It realizes new time-series semantic similarity by comparison with Kansei transitions represented by waveforms applying a signal processing technique— the DTW distance shown in Section 2.2. Using the semantic waveform similarity measurement makes it possible to realize media content retrieval and recommendation systems corresponding to the time-series Kansei transition of media content.

Figure 8 shows the realization methods for the Semantic waveform similarity measurement module. This module consists of two steps.

(1) Computing DTW distance in each Kansei element

The Kansei transition extraction module outputs waveforms as Kansei transition from time-series media content. It computes the DTW distance in each Kansei element. This means computing the similarity of each single waveform for each Kansei element.

(2) Composition of each DTW distance

It composes each DTW distance derived in (1). The composition value is a multiple waveform similarity value for Kansei transition.

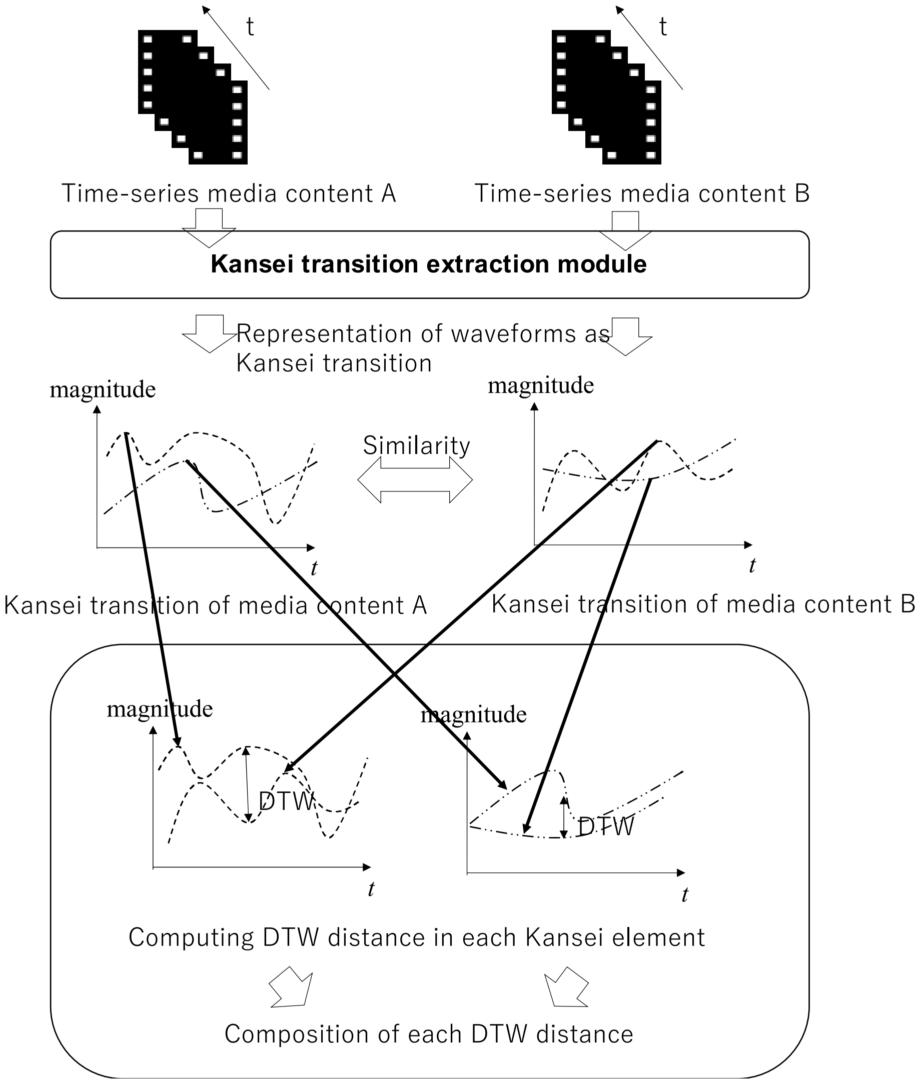

Figure 8: An overview of the waveform similarity computation module. The Kansei transition extraction module outputs waveforms as Kansei transition from time-series media content. In order to compute similarity of Kansei transition, the module computes DTW distance in each Kansei element. Finally, the module composes each DTW distance. The composition value is a Semantic waveform similarity measurement for Kansei transition.

3.4 Example of the Application of Semantic Waveform Measurement Method to Text Data such as a Novel

In this section, we represent an example of the application of semantic waveform measurement method to text data such as a novel in Japanese. Generally, a novel changes the impression you get depending on which part of the text you are reading. We extract the change of the impression as Kansei Transition in a novel and realize the similarity measurement between novels based on the storyline of the novel.

3.4.1 Kansei transition extraction module using negative-positive word recognition for text data

The one of the methods for extraction Kansei element from text data is the sentiment analysis to determine the negatives and positives of words. In this paper, a Japanese polarity dictionary [10][11] is used to sentiment analysis of a word. We refer to the Japanese polar dictionary and determines the negative-positive for each word in the text data. We represent the results as a number, -1 for negative, +1 for positive. The Kansei Transition is extracted by calculating the average of the sentiment analysis results for each word in each sentence, and then calculating the moving average for each of the five sentences.

The Kansei transition extraction module for text data consists of four steps.

(1) Dividing media content according to a specified window size

It divides the text data at regular intervals according to a specific window size to obtain time-series characteristics from the text data. In this case, we use the window size for each sentence and also take a moving average for each of the five sentences.

(2) Extracting sentiment value from each sentence

It extracts features from each sentence divided in (1) as a characteristic of the text data for each time. Each sentence consists of some words and each sentence is represented by a vector in a bag of words. These extracted T features are represented as the $n \times T$ media content matrix X in Figure 5. The n is the number of occurrences of the word.

(3) Transforming from features to Kansei elements

It converts the sentiment values corresponding to the media content matrix X extracted in (2). The results of sentiment analysis are expressed as a sentiment value between -1 and 1. It extracts a sentiment value from each sentence divided in (1) as a characteristic of the text data for each time. In addition, we obtain a moving average for each of the five sentences at each time. In this case, the transformation matrix in Figures 5 is represented as $1 \times n$ matrix. In Figures 5, we can generate the matrix Y represented as $1 \times n$.

(4) Representing waveforms as Kansei transition

It represents one waveform as Kansei transition. The waveform represents sentiment values for each time. When sentiment values are plotted on the time axis, waveform are visualized.

3.4.2 Semantic waveform similarity measurement module for text data

This Kansei transition extraction module extracts Kansei transitions, which represent the emotional movements of each novel text data. In this case, the Kansei Transition extracted from each novel text data consists of a single waveform. It realizes new time-series semantic similarity by comparison with Kansei transitions represented by waveforms applying a signal processing technique— the DTW distance shown in Section 2.2. Using the semantic waveform similarity measurement makes it possible to realize text data retrieval and recommendation systems corresponding to the time-series Kansei transition of media content.

The Kansei transition extraction module outputs a single waveform as Kansei transition from time-series media content. It computes the DTW distance. This means computing the similarity of each single waveform.

4 Experiment

In this section, we implement the semantic waveform measurement method by Kansei transition for the novel text data shown in Section 3.4 and compute the similarity by the semantic waveform measurement method based on Kansei transition using the famous Japanese novels "Wagahai ha Nekodearu", "Sanshiro", and "Kokoro" written by Soseki Natsume.

First, we extract each Kansei transition of "Wagahai ha Nekodearu", "Sanshiro", and "Kokoro" by Kansei transition extraction module using negative-positive word recognition for text data as shown in Figure 9, 10, and 11.

Here, by Figure 9, 10, and 11, since the length of each novel is different, the length of the extracted Kansei transition is also different. The semantic waveform similarity measurement module uses DTW distance to perform the calculation, therefore it is possible to compute distance measurement between waveforms with different lengths.

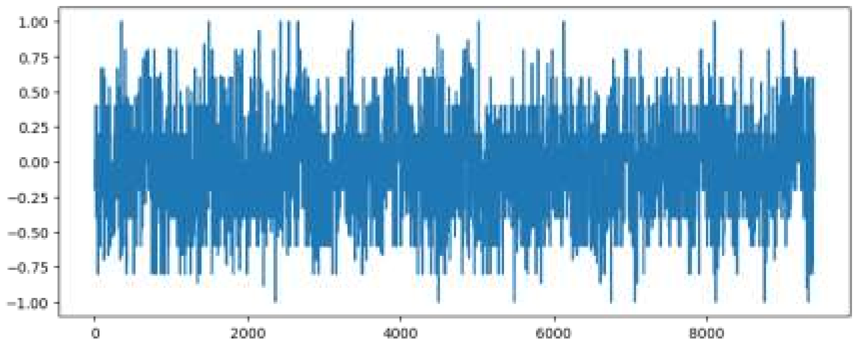

Figure 9: Exracted Kansei transition from "Wagahai ha Nekodearu"
(Horizontal axis: number of articles, vertical axis: sentiment values)

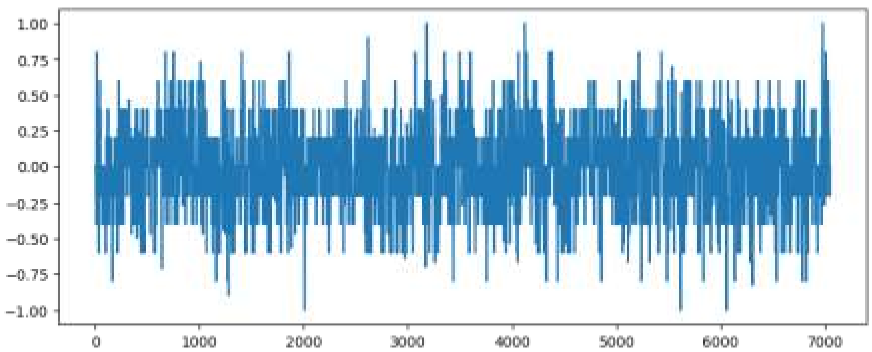

Figure 10: Exracted Kansei transition from "Sanshiro"
(Horizontal axis: number of articles, vertical axis: sentiment values)

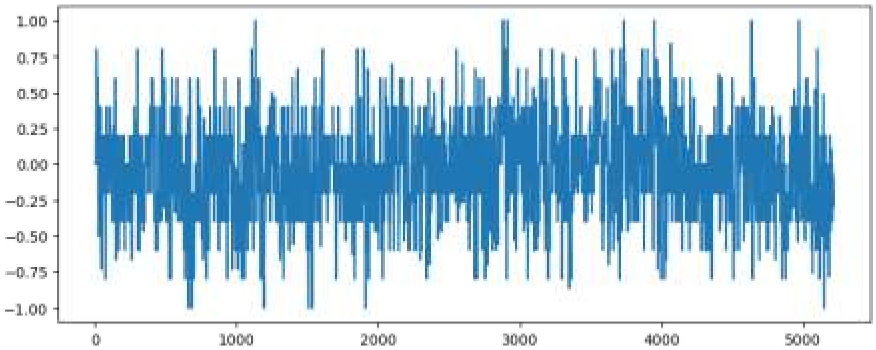

Figure 11: Exracted Kansei transition from “Kokoro”
(Horizontal axis: number of articles, vertical axis: sentiment values)

The distance measurement results of the novels, "Wagahai ha Nekodearu", "Sanshiro", and "Kokoro" using the semantic waveform measurement method are shown in Table 1.

Table1: Result of Semantic waveform similarity measurement

	Wagahai ha Nekodearu	Sanshiro	Kokoro
Wagahai ha Nekodearu	0.0	1048.42	1070.30
Sanshiro	–	0.0	693.95
Kokoro	–	–	0.0

Since the semantic waveform measurement is a distance, the smaller the value, the higher the similarity. The results of the semantic waveform measurement show that "Sanshiro" and "Kokoro" are more similar than "Wagahai ha Nekodearu". This means that the storylines of "Sanshiro" and "Kokoro" are similar, while "Wagahai ha Nekodearu" has a different storyline from "Sanshiro" and "Kokoro". This system recommends appropriate novels by the similarity of the negative-positive changes in the story, as opposed to simply weighing the similarity by TF/IDF or other weights across novels. In other words, this system realizes a similarity metric based on the storyline that each novel has. This measurement method makes use of the time-series changes of the novel.

The semantic waveform measurement method is a new similarity metric for media contents such as novels, music, and videos with time-series variation. Media content with chronological change gives humans a change in sensitivity— Kansei transition. Searching, recommending, and presenting media content based on the Kansei transition is important because it has a time-series change and explores the storyline.

In this experiment, we realized the similarity measure of the Kansei transition consisting of single waveform, however it is important to realize the similarity measure of the Kansei transition consisting of multiple waveforms in order to express various meanings and sensitivities. The implementation of the semantic waveform measurement method between Kansei transitions consisting of multiple waveforms is a future issue.

5 Conclusion

In this paper, we presented a semantic waveform measurement method of Kansei transition for time-series media contents. It is important to apply time-series change of media content to Kansei information processing. In our method, we represent Kansei transition by time-series change of media content as waveforms. We realize semantic waveform measurement by comparison with Kansei transitions represented by waveforms applying a signal processing technique. The semantic waveform measurement makes it possible to realize media content retrieval and recommendation systems corresponding to the time-series Kansei transition of media content.

We represent an example of the application of semantic waveform measurement method to text data such as a novel. We implement the semantic waveform measurement method by Kansei transition for the novel text data shown in Section 3.4 and compute the similarity by the semantic waveform measurement method based on Kansei transition using the famous Japanese novels.

The Kansei transition extraction module extracts time-series Kansei magnitude from the features of time-series media contents as Kansei transition. The semantic waveform similarity measurement module measures similarities between each waveform represented as Kansei transition. Our method enables to calculate the similarity of media content based on time-series changes in Kansei. We can apply our method to new media content retrieval depending on time-series change in media content Kansei.

In the near future, our method will be applied to other media content environments. We must the implementation of the semantic waveform measurement method between Kansei transitions consisting of multiple waveforms. Furthermore, we must consider how to calculate similarity of multiple waveforms by using the DTW distance at low cost.

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