Morphable Word Clouds for Time-Varying Text Data Visualization

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Abstract—A word cloud is a visual representation of a collection of text documents that uses various font sizes, colors, and spaces to arrange and depict significant words. The majority of previous studies on time-varying word clouds focuses on layout optimization and temporal trend visualization. However, they do not fully consider the spatial shapes and temporal motions of word clouds, which are important factors for attracting people's attention and are also important cues for human visual systems in capturing information from time-varying text data. This paper presents a novel method that uses rigid body dynamics to arrange multi-temporal word-tags in a specific shape sequence under various constraints. Each word-tag is regarded as a rigid body in dynamics. With the aid of geometric, aesthetic, and temporal coherence constraints, the proposed method can generate a temporally morphable word cloud that not only arranges word-tags in their corresponding shapes but also smoothly transforms the shapes of word clouds over time, thus yielding a pleasing time-varying visualization. Using the proposed frame-by-frame and morphable word clouds, people can observe the overall story of a time-varying text data from the shape transition, and people can also observe the details from the word clouds in frames. Experimental results on various data demonstrate the feasibility and flexibility of the proposed method in morphable word cloud generation. In addition, an application that uses the proposed word clouds in a simulated exhibition demonstrates the usefulness of the proposed method.

Index Terms—Word cloud, time-varying text data, digital storytelling, information visualization

1 Introduction

Recent developments of Web 2.0 and Internet techniques have yielded an increasing amount of information on web-based data-sharing platforms. How to provide a pleasing summarization for a huge text data has thus become an important research topic in information visualization. Word clouds are text-based visual representations that display word significance in terms of popularity and importance by using different font sizes and colors. Word clouds can be used as website navigation aids sometimes for the purpose of advertisement, in which a hyperlink to a related or advertised term is attached with a word-tag [1], [2]. Thus, word clouds serve as visual tools that attract and aid people to navigate information. Word clouds can also evolve as the associated data sources change over time [3]. To encode temporal trends in word clouds, previous studies have introduced parallel word clouds or combined word clouds with a trend curve [3], [4], [5], [6]. These strategies significantly improve the trend visualization of time-varying data. In this study, we further consider how to present temporal motions and spatial shapes in time-varying word clouds to achieve a pleasing and engaging visual representation.

Morphing (or animation) that contains smooth transitions of shapes and content is an intuitive way for human visual systems to perceive time-varying data. For instance, a sequence of shapes depicting the human evolution from Australopithecine to Homo sapiens (Fig. 1) is an intuitive way of explaining the human evolutionary process. Based on this observation, we combine a time-varying text document with its corresponding shape sequence to generate a morphable word cloud, that is, a time-varying word cloud arranged in a shape sequence, in which the temporal changes in both word-tags and shapes of the word clouds are visualized. To achieve this goal, the proposed method includes algorithms for generating a smooth shape sequence from several key-shapes and for arranging word-tags in their corresponding shapes in accordance with various constraints.

To provide flexible control over word-tag layouts, the technique of rigid body dynamics is utilized. Each word-tag is viewed as a rigid body with a mass. Given a set of constraints in boundary, temporal coherence, and word-tag distribution, the dynamics can arrange a time-varying word cloud in a specific shape sequence. We also introduce position and orientation constraints into the dynamics to provide flexible control over word clouds.

Word clouds are sometimes not as effective as word lists in alphabetical or occurrence frequency order, in term of easiness of information finding [7], [8], [9]. However, providing an engaging representation is also important in word cloud generation. For instance, several recent studies [10], [11], [12] propose using aesthetic criteria to create an appealing word-tag layout. In this study, by combining

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Manuscript received 1 Sept. 2014; revised 27 Apr. 2015; accepted 17 May 2015. Date of publication 3 June 2015; date of current version 26 Oct. 2015. Recommended for acceptance by H. Qu.
For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org, and reference the Digital Object Identifier below.
Digital Object Identifier no. 10.1109/TVCG.2015.2440241

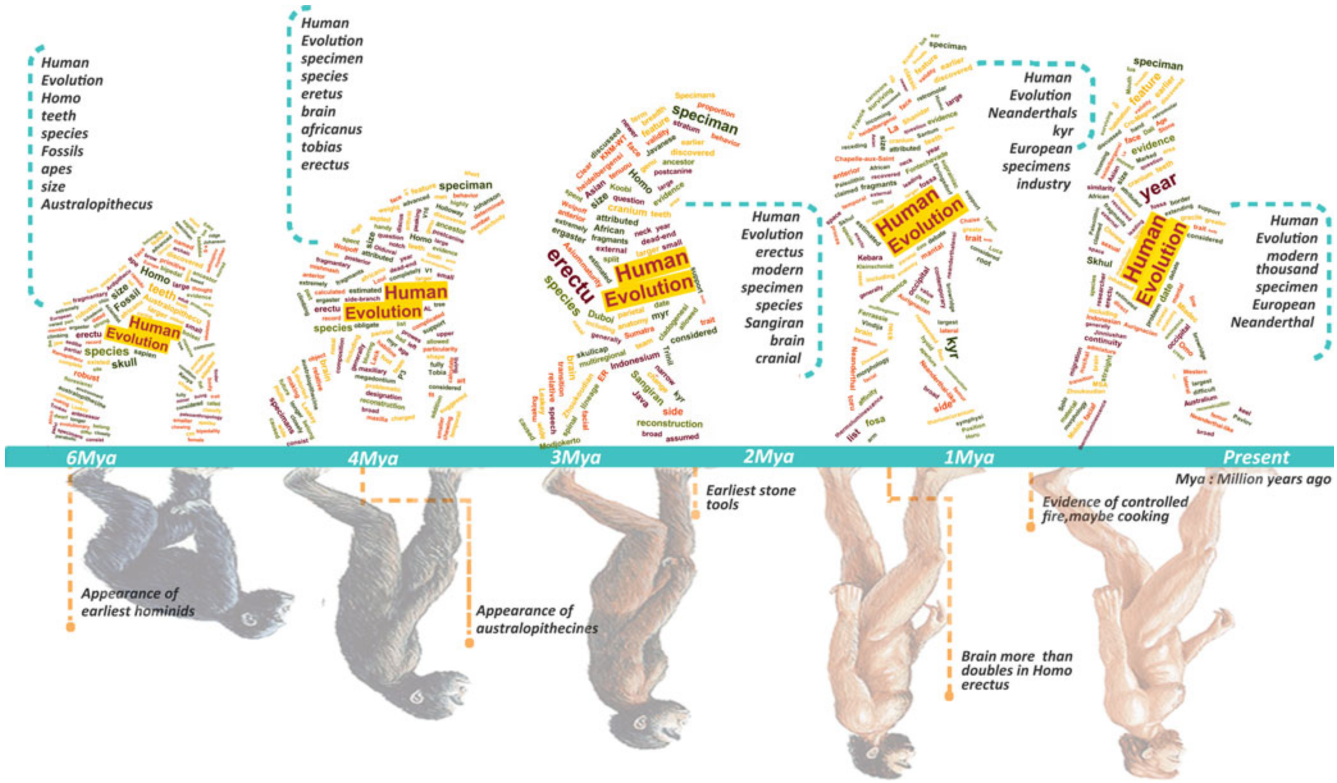

Fig. 1. Morphable word cloud depicts the human evolution from Australopithecine to Homo sapiens. This time-varying word cloud can serve as a storytelling and visualization tool to illustrate the human evolutionary process.

shape morphing with word clouds, the proposed method can generate an interesting and engaging representation for a time-vary text document, thereby making it suitable for advertisement and exhibition, as illustrated in Fig. 2.

In summary, compared with related work on static word clouds [10], [12], [13] and spatial-temporal word clouds [5], this study provides the contribution of generating a frame-by-frame and morphable word cloud that can smoothly represent the temporal changes in both the shapes and content of word clouds. People can observe the overall story of a time-varying text data from the shape transition, and people can also observe the details such as word-tag changes from the word clouds in frames by pausing, enlarging, or slowing down the morphing. Thus, the proposed word clouds can serve as visualization and storytelling tools used in advertisement and exhibition. The remainder of this paper is organized as follows. Section 2 reviews the related work. Section 3 presents the proposed methods. Sections 4 and 5 discuss the experimental results and user studies. Section 6 presents the conclusions, limitations, and suggestions for future work.

Fig. 2. Simulated exhibition using our morphable word clouds.

2 Related Work

Numerous text-based visualization methods have recently been proposed. These methods can be classified into two categories, namely, *static word cloud* and *time-varying word cloud*, based on the temporal characteristics of the input documents. In static word clouds, the occurrence frequency of a word is encoded into its font size in the summarization of a text collection. Viegas et al. [10] propose a text-based visualization system called Wordle, which exploits a greedy-based space filling approach to create word clouds while maintaining the word-tags' features, such as occurrence frequency and significance, by using font size. Wordle also exploits color, typography, and composition to enrich word-tag layouts. ManiWordle [12] and Rolled-out Wordle [11] adopt a spiral growth placement strategy in word-tag arrangement and provide a flexible manipulation of word-tag layouts for an interactive system. These methods attempt to provide an editing tool for static word clouds while maintaining aesthetic layouts. In addition, a number of studies have improved the analysis and layout of text data to attain an enhanced understanding of complex text data. Cui et al. [5] analyze the relation among word-tags and use a force-directed model to achieve context preservation. Cao et al. [14] present a multifaceted visualization system, called FacetAtlas, which visualizes global and local relations of complex text collections by using graphs with density maps. Wu et al. [13] adopt seam carving technique to iteratively remove a seam from a layout in order to

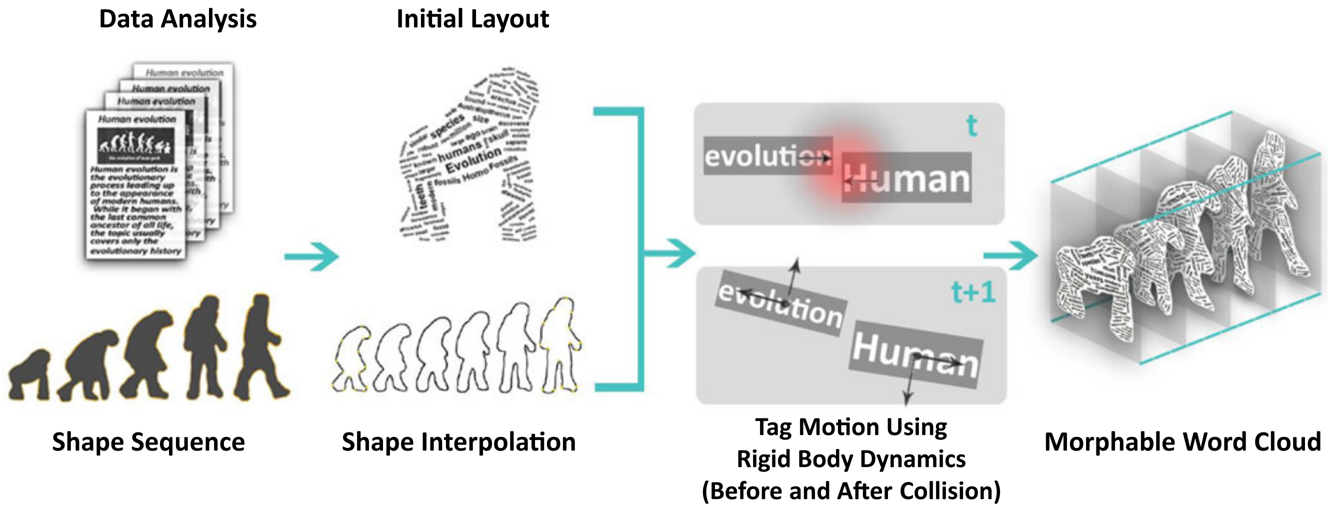

Fig. 3. System workflow. The input to our system is a set of text documents and a shape sequence. After data analysis, shape interpolation, and word layout initialization, a morphable word cloud in a specific shape sequence is generated by using rigid body dynamics.

generate semantic-preserving and compact word clouds, and Paulovich et al. [15] generate a semantically consistent layout through a multidimensional projection. Strobelt et al. [16] propose a novel compact visualization that represents a document as a mixture of images and several extracted key terms. Recently, Maharik et al. [17] view word clouds as text-art works, and propose a method to create fancy digital micrograph images, that is, text mosaicking, from minuscule text. Afzal et al. [18] combine text and spatial data in a typographic map. With the layout optimization, the aforementioned methods can yield good word clouds in terms of aesthetics or compactness arrangement. However, these methods cannot be applied to time-varying text documents easily.

The main differences of time-varying word clouds from static word clouds are the visualization of temporal trends and the preservation of temporal coherence. Graphs with multiple lines and stacked bar charts are traditional tools for temporal change representation. Havre et al. [19] propose the use of colored lines with various widths to visualize thematic variations over time. Shi et al. [20] combine trend graphs with word clouds to represent large corpora of texts. Dubinko et al. [21] adopt river and waterfall metaphor to dynamically visualize the evolution of tags on Flickr. Collins et al. [4] and Culy et al. [6] combine the visualization tools of parallel coordinates and word clouds to provide a visual summary of a text collection in a specific time period. Similarly, Lee et al. [3] introduce a text visualization tool, called SparkClouds, which integrates sparklines with word clouds to convey the changes across multiple word clouds. Cui et al. [5] combine a global trend chart with multiple static word clouds in several time stamps to express timeline changes. Although these methods can generate trend visualization results, the spatial information and temporal changes are represented in static images. By contrast, in the proposed method, the spatial-temporal information of a text collection is represented in a morphable word cloud, thus providing a continuous and pleasing spatial-temporal visualization. In addition, the word-tags are arranged in a specific shape sequence which is an important cue in understanding the overall story of a time-varying data.

3 Methodology

Fig. 3 illustrates the proposed morphable word cloud generation which consists of three main steps: *data preprocessing*, *shape sequence generation*, and *word cloud motion generation*. The input to the proposed method is a set of text documents with a sequence of corresponding key-shapes. This study aims to generate a morphable word cloud, in which extracted keywords are arranged in their corresponding shapes. At preprocessing stage, document analysis is performed to extract significant words from input text documents. Note that we focus on the morphable word cloud generation rather than analyzing word and semantic significances. Therefore, significant words are extracted simply based on the occurrence frequency of each word after a text document is tokenized into a set of words. For more details on the significance analysis, please refer to [5], [13]. In shape sequence generation, a simple interface with the function of feature point selection is provided for users to define the mapping between the boundaries of two key-shapes. The intermediate shape boundaries are then generated through linear interpolation. Thereafter, the rigid body dynamics is performed to arrange the extracted words in theirs corresponding shapes under various constraints. The shape interpolation, word layout initialization, time-varying word cloud generation, and dynamics solver are described in Sections 3.1, 3.2, 3.3, and 3.4, respectively.

3.1 Shape Interpolation

Shape morphing refers to a smooth shape transformation sequence that transforms a shape into another through a seamless transition. In this study, the boundaries of a shape morphing sequence are used as boundary constraints in generating time-varying word clouds. Thus, shape interpolation is reduced to boundary interpolation. Given two boundary contours C^A and C^B which are extracted from two consecutive key-shapes of genus-0 (a shape without holes inside) by using image morphology techniques, several pairs of corresponding feature points $\{(p_i^A, p_i^B)\}_{i=1}^{n_f}$ on the boundaries of key-shapes are specified by users through a simple interface, where n_f represents the number of

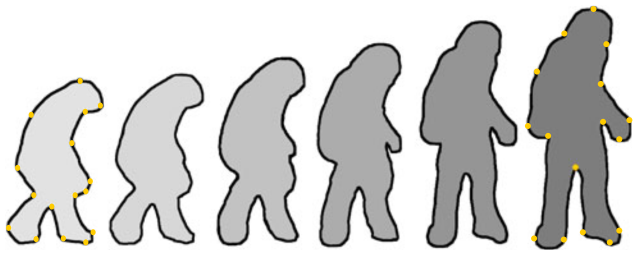

Fig. 4. Result of boundary contour interpolation. The first and last figures are the boundary contours extracted from key-shapes, and the yellow points are the user-specified feature points.

feature points. The correspondences of the other boundaries (i.e., the unmatched boundaries) are determined by linearly interpolating the neighboring corresponding feature points. The intermediate boundary contours are then interpolated by using linear interpolation with the determined correspondence. In this manner, a sequence of boundary contours can be obtained from the input key-shapes (Fig. 4). Note that this study focuses on time-varying layouts, and thus a simple shape interpolation is adopted. If an elegant shape sequence is required, an advanced shape interpolation method such as [22] can be adopted.

3.2 Word Layout Initialization

The input text documents are tokenized into a collection of words. Low-significance words such as "in", "the", and "he/she" are filtered out first, and significant words are extracted on the basis of the occurrence frequencies of the words. The occurrence frequency of the ith word at time t , denoted by $freq_i^t$, is normalized to [0, 1], and the font size of this word at time t is determined by

$$fsize_i^t = T_{min} + (T_{max} - T_{min}) \times freq_i^t, \tag{1}$$

where T_{max} and T_{min} denote the maximal and minimal font sizes, respectively. T_{max} and T_{min} are tunable parameters and are initially set to 100 and 10, respectively. In addition, a tunable parameter T_d ranging from 50 to 95 is provided for users to determine the word-tag denseness. This parameter is initially set to 80, which means 80 percent space is used.

An initial word-tag placement is required in the proposed method only for the extracted words of the initial time $(t = 0)$. The other extracted words are included dynamically in the dynamics process over time. In the implementation, similar to [10], a greedy-based space filling approach is adopted. The words appearing at the initial time are placed from the center to the boundary of the shape in order of word significance. Note that an initial placement containing overlaps is allowed because the overlaps can be released by using contacting constraints in the dynamics.

3.3 Time-Varying Word Cloud Generation

3.3.1 Review of Rigid Body Dynamics

The proposed method is based on rigid body dynamics [23], [24]. This section thus begins with a brief introduction of this technique. In rigid body dynamics, a state vector $\mathbf{Y}(t) = (\mathbf{x}(t), \mathbf{R}(t), \mathbf{L}(t), \mathbf{A}(t))$ is defined to describe the states of bodies (i.e., word-tags) at time t, where $\mathbf{x}(t)$ and $\mathbf{R}(t)$ represent the positions and orientations of word-tags (describing spatial information), respectively, and $\mathbf{L}(t)$ and $\mathbf{A}(t)$ denote the linear and angular momentums (describing velocity information), respectively. The manipulation of this state vector is vital in dynamics computation. The entries in the state vector are thus described first, followed by the proposed constraints and the numerical solver for the state vector. To simplify the equations, the mass center is assigned to the origin of the word-tag space (i.e., a local space). In this geometric setting, $\mathbf{x}(t)$ represents the position of the mass center in world space and $\mathbf{R}(t)$ denotes the rotation matrix of a word-tag about the origin of the word-tag space. The velocity of the mass center in world space is obtained by calculating the derivative of $\mathbf{x}(t)$, that is, $\mathbf{v}(t) = \dot{\mathbf{x}}(t)$. In the velocity information description, word-tag spinning is represented by a vector $\boldsymbol{\omega}(t)$ that passes through the origin of the word-tag space. This vector provides the direction of the axis about word-tag spinning. The magnitude of this spanning vector, that is, $|\boldsymbol{\omega}(t)|$, represents the spinning velocity of the word-tag. In other words, $\boldsymbol{\omega}(t)$ is the angular velocity and $|\boldsymbol{\omega}(t)|$ is the magnitude of the angular velocity.

Assuming that a word-tag consists of n_p particles, i.e., the smallest element in the word-tag space, the mass of the ith particle is m_i, and the position of this particle related to the center of mass $x(t)$ in the word-tag space is $\hat{\mathbf{r}}_i$. The position of this particle in the world space at time t, denoted as $\mathbf{r}_i(t)$, is therefore formulated as

$$\mathbf{r}_i(t) = \mathbf{R}(t)\hat{\mathbf{r}}_i + \mathbf{x}(t). \tag{2}$$

The total mass of the word-tag is the sum $M = \Sigma_{i=1}^{n_p} m_i$, and the velocity $\dot{\mathbf{r}}_i(t)$ of the ith particle can be formulated by using the relation $\dot{\mathbf{R}}(t) = \boldsymbol{\omega}(t) \times \mathbf{R}(t)$ as

$$\dot{\mathbf{r}}(t) = \boldsymbol{\omega}(t) \times \mathbf{R}(t)\hat{\mathbf{r}}_i + \mathbf{v}(t). \tag{3}$$

In consideration of the external forces in dynamics, the total external force acting on the ith particle at time t is denoted by $\mathbf{F}_i(t)$, and the external torque $\boldsymbol{\tau}_i(t)$ acting on the ith particle is then defined by $\boldsymbol{\tau}_i(t) = (\mathbf{r}_i(t) - \mathbf{x}(t)) \times \mathbf{F}_i(t)$. According to this definition, the total external force acting on a word-tag is the sum $\mathbf{F}(t) = \sum_i \mathbf{F}_i(t)$ and the total external torque can be obtained by

$$\boldsymbol{\tau}(t) = \sum_i (\mathbf{r}_i(t) - \mathbf{x}(t)) \times \mathbf{F}_i(t). \tag{4}$$

Two kinds of momentums, namely, linear and angular momentums, are used in dynamics. The assumption of body rigidity allows the linear and angular velocities of all the particles to be the same. According to Newton's second law, the linear momentum $\mathbf{l}$ of a particle with mass m and velocity $\mathbf{v}$ is defined by $\mathbf{l} = m\mathbf{v}$. Thus, the total linear momentum $\mathbf{L}(t)$ of a rigid word-tag is the sum of the products of the mass and velocity of each particle, that is,

$$\mathbf{L}(t) = \sum_i m_i \dot{\mathbf{r}}_i(t) = \left(\sum_i m_i\right)\mathbf{v}(t) = M\mathbf{v}(t), \tag{5}$$

where M represents the mass of the word-tag. M is a constant and $\dot{\mathbf{L}}(t) = \mathbf{F}(t)$; therefore, we can derive

$$\dot{\mathbf{v}}(t) = \dot{\mathbf{L}}(t)/M = \mathbf{F}(t)/M. \tag{6}$$

The physical relation $\mathbf{L}(t) = M\mathbf{v}(t)$ can be obtained through linear momentum deduction. According to this relation, the total angular momentum $\mathbf{A}(t)$ of a rigid word-tag is similarly defined as

$$\mathbf{A}(t) = \mathbf{I}(t)\boldsymbol{\omega}(t), \tag{7}$$

where $\mathbf{I}(t)$ denotes an inertial tensor describing how the mass in a word-tag is distributed relative to the mass center of the word-tag. Analogous to the relation $\dot{\mathbf{L}}(t) = \mathbf{F}(t)$, the derivative of the angular momentum is formulated as $\dot{\mathbf{A}}(t) = \boldsymbol{\tau}(t)$. The inertial tensor is the scaling factor between the angular momentum and the angular velocity. At a given time t, let $\hat{\mathbf{r}}_i$ be the translation of the ith particle from $\mathbf{x}(t)$, that is, $\hat{\mathbf{r}}_i = \mathbf{r}_i(t) - \mathbf{x}(t)$. The inertial tensor is formulated in terms of $\hat{\mathbf{r}}_i$ as the symmetric matrix:

$$\mathbf{I}(t) = \mathbf{R}(t)\mathbf{I}_{tag}\mathbf{R}(t)^T, \tag{8}$$

where $\mathbf{I}_{tag} = \sum_{i=1}^{N} m_i(\hat{\mathbf{r}}_i^T\hat{\mathbf{r}}_i\mathbf{I}_0 - \hat{\mathbf{r}}_i\hat{\mathbf{r}}_i^T)$ and $\mathbf{I}_0$ represents an identity matrix. $\mathbf{I}_{tag}$ is a constant over the word-tag motion because $\mathbf{I}_{tag}$ is specified in the word-tag space. $\mathbf{I}_{tag}$ can thus be computed during preprocessing and $\mathbf{I}(t)$ can be obtained from $\mathbf{I}_{tag}$ and the rotation matrix $\mathbf{R}(t)$.

According to the abovementioned description, the derivative of the state vector $\frac{d}{dt}\mathbf{Y}(t)$ can be obtained by

$$\frac{d}{dt}\mathbf{Y}(t) = \frac{d}{dt}\begin{bmatrix}\mathbf{x}(t)\\ \mathbf{R}(t)\\ \mathbf{L}(t)\\ \mathbf{A}(t)\end{bmatrix} = \begin{bmatrix}\mathbf{v}(t)\\ \boldsymbol{\omega}(t)\times\mathbf{R}(t)\\ \mathbf{F}(t)\\ \boldsymbol{\tau}(t)\end{bmatrix}, \tag{9}$$

where the auxiliary terms in Eq. (9) are computed by using $\mathbf{v}(t) = \mathbf{L}(t)/M$, $\mathbf{I}(t) = \mathbf{R}(t)\mathbf{I}_{tag}\mathbf{R}(t)^T$, $\boldsymbol{\omega}(t) = \mathbf{I}(t)^{-1}\mathbf{A}(t)$, and Eq. (4). Given a state vector, Eq. (9) describes how the state vector is instantaneously changing. The dynamics starts with an initial condition of $\mathbf{Y}(0)$ (i.e., $\mathbf{x}(0)$, $\mathbf{R}(0)$, $\mathbf{L}(0)$, and $\mathbf{A}(0)$), and then a numerical solver which is described in Section 3.4 is used to track the change of the state vector (i.e., $\frac{d}{dt}\mathbf{Y}(t)$) over time.

3.3.2 Constrained Rigid Body Dynamics

This section addresses the problems that arise when a uniformly distributed word cloud in a specific shape is required, overlapping between word-tags is disallowed, and word cloud editing and temporal coherence of time-varying word clouds are required. In view of these problems regarding word-tag temporal motion and spatial placement, constrained rigid body dynamics is adopted, and six constraints, namely, *contacting constraint*, *uniform constraint*, *boundary constraint*, *orientation constraint*, *position constraint*, and *temporal coherence constraint* are introduced in the dynamics system with an iterative solver. Among these constraints, the orientation, position, and temporal coherence constraints are new constraints imposed in the dynamics to provide flexible manipulations and temporal-coherence arrangements. These constraints are described as follows.

Contacting constraint. This constraint is used to avoid word-tag overlapping and is achieved by computing and assigning appropriate contact forces to contacting word-tags. To find the contacting word-tags, the process of collision

Fig. 5. Word clouds without (left) and with (right) boundary constraints.

detection is required. A convex polyhedral with bounding box hierarchy is created for each word-tag, and any efficient algorithm such as the methods presented in [23] can be adopted to detect word-tag collisions. When two word-tags are moving toward each other and are in contact at a point (this situation is called colliding contact), an instantaneous change in velocity is computed and assigned to these two word-tags. If collision occurs at time t, the dynamics process is temporarily stopped, and the current state vector ($\mathbf{Y}(t)$) is extracted. The velocities and moving directions of the contacting word-tags are recomputed such that the contacting word-tags are bounced off each other. The numerical solver is restarted by using the new state vector. Please refer to [23] for details on recalculating the velocity and state vector.

Boundary constraint. A boundary constraint is used to arrange word-tags in a specific shape. The boundary contours of the input key-shapes are extracted by using image morphology techniques, and a boundary sequence is generated by using linear interpolation (described in Section 3.1). The basic idea of this constraint is to view boundary pixels as static bodies in the dynamics system. In other words, the pixels on the boundary of the shape behave like fixed-position word-tags in the cloud, and the word-tags that are in contact with the boundary bodies are totally rebounded. Note that static bodies, i.e., boundary vertices, can be skipped in the calculation of the state vector. Therefore, a static body is not equal to a fixed-position rigid body in dynamics system. A comparison of word-tag layouts with and without boundary constraint is shown in Fig. 5. With the boundary constraints, the proposed system can generate a word cloud of a specific shape.

Uniform constraint. A uniform constraint is used to generate a uniformly distributed layout. The basic idea is to insert several virtual bodies with attracting forces in empty regions. These virtual bodies are used to attract neighboring bodies to empty regions. A virtual body is a rectangular empty region which is determined by using summed area table, a data structure and algorithm used to efficiently calculate the number of empty pixels in a rectangular subset of a layout [25]. In each iteration of the dynamics process, a fixed virtual body is dynamically inserted in an empty region. The mass of a virtual body, denoted by M_v, is defined as the area of the empty region. According to Newton's law of universal gravitation, two bodies attract each other with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them. For a word-tag o_j with mass M_j, the attracting force $\mathbf{F}_{uniform}$ from the virtual body v_i is defined as

Fig. 6. Demonstration of the use of uniform constraint. Left: word cloud without uniform constraints; right: word cloud with uniform constraints. The gray region represents the specified shape of the layout.

$$\mathbf{F}_{uniform}(v_i, o_j) = \frac{M_v M_j \vec{\mathbf{u}}}{\|x_{v_i} - x_j\|^2}, \tag{10}$$

where x_{v_i} and x_j are the positions of v_i and o_j, respectively; $\vec{\mathbf{u}}$ is the normalized vector of $(x_{v_i} - x_j)$. With the aid of this constraint, the proposed dynamics system can generate a word layout as uniformly as possible, resulting in an pleasing visualization (as shown in Fig. 6).

Orientation constraint. Orientation and position constraints are introduced in the dynamics to facilitate flexible editing on word clouds, which are similar to the interactive functions in ManiWordle [12]. The orientation constraint allows users to constrain the orientations and directions of word-tags in the arrangement. This constraint is achieved by assigning a rotation matrix to the word-tags and fixing their angular momentums, that is, setting $\mathbf{A}(t) = \mathbf{0}$. For instance, in Fig. 7, the word clouds arranged in horizontal, diagonal, vertical, and arbitrary directions are created by using our method with this constraint. Besides, to avoid generating an upside down word-tag and reducing the readability level, the angles and ordinations of word-tags are bounded at [-90, 90]. A comparison of word-tag layouts with and without angle constraints is shown in Fig. 8. With the angle constraints, the word-tag flipping problem is solved.

Position constraint. Similar to the orientation constraints, the proposed method allows users to specify the positions of word-tags by fixing the word-tag positions and freezing their linear momentums (i.e., $\mathbf{L}(t) = \mathbf{0}$). For instance, in Fig. 9, the position of the word-tag "Human" is fixed in the word cloud motion.

Temporal coherence constraint. Maintaining temporal coherence is important in time-varying data visualization. In the proposed dynamics, the temporal coherence of a multi-temporal word-tag, that is, a word-tag appearing in word clouds for a certain period, is maintained by adding a coherent force to this word-tag. Similar to the virtual bodies described in the uniform constraint, this force attracts a

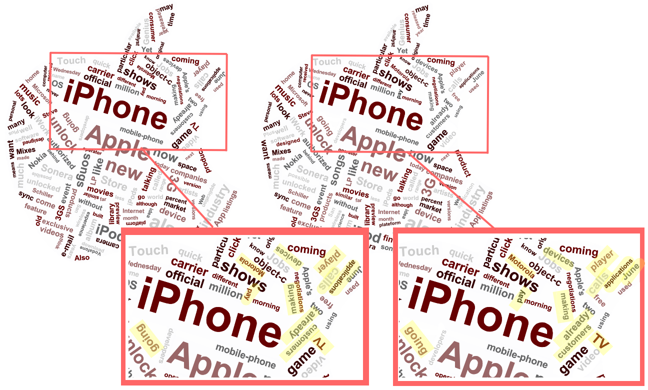

Fig. 8. Word-tag flipping problem. The problems of upside-down word-tags (left) are avoided by using orientation constraints (right).

word-tag to its predetermined position. Given a word-tag o_i, its position at time t is denoted by $x_i(t)$. We determine the initial position of the word-tag o_i at time $t+1$ by using mean value coordinate [26], that is,

$$x_i(t+1) = \sum_{j=1}^{n_f} w_j p_j^{t+1}, \tag{11}$$

where $\sum_{j=1}^{n_f} w_j = 1$ and $w_1, \ldots, w_{n_f}$ are the coefficients of the mean value coordinate of the word-tag o_j. The coefficient w_j is defined as the inverse distance between o_i and the boundary feature point p_j. Specifically, the coefficients $w_1, \ldots, w_{n_f}$ of a word-tag is obtained at time t through $x_i(t)$ and the boundary feature points $\{p_1, \ldots, p_{n_f}\}$, then the initial position of this word-tag at time $t+1$, that is $x_j(t+1)$, is calculated by using Eq. (11). In addition to the initial position assignment, an external force, denoted by $\mathbf{F}_{temporal}$, is applied to a multi-temporal word-tag such that this word-tag is attracted to its initial position. Similar to the attracting force in Eq. (10), this coherent force is directly proportional to the mass of the multi-temporal word-tag and inversely proportional to the square of the distance between the initial position and the current position of this word-tag, that is,

$$\mathbf{F}_{temporal}(o_i) = \frac{M_i \vec{\mathbf{c}}}{\|\hat{x}_i - x_i\|^2}, \tag{12}$$

where x_i and $\hat{x}_i$ denote the current and initial positions of the word-tag o_i, respectively; $\vec{\mathbf{c}}$ is the normalized vector of $(\hat{x}_i - x_i)$. Note that the predetermined position is an initial position and the temporal coherence constraint is a soft constraint. The position of a word-tag may be arranged far from its predetermined position when word-tags change

Fig. 7. Orientation constraint demonstration. From left to right: word clouds arranged in horizontal, diagonal, vertical, and arbitrary directions.

Fig. 9. Position constraint demonstration. The position of the word-tag "human" is fixed in the word cloud motion.

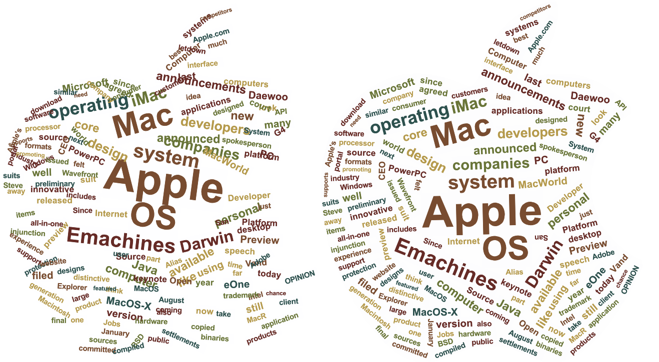

Fig. 10. Overlap-free word cloud. Overlapping word-tags (left) can be released by the proposed method (right).

significantly with respect to its significance value and tag size. In this rare case, the word-tag sizes are maintained while the temporal coherence is preserved as much as possibly in our system. In addition, fade-in and fade-out effects are applied to the appearing and disappearing word-tags, respectively, to ensure a smooth transition.

3.4 Dynamics Solver

The process of the rigid body motion is described in the pseudocode. The dynamics process starts with an initial condition of the state vector of the rigid bodies ($\mathbf{Y}(0)$). The initial positions of the word-tags at the initial time ($t = 0$) are calculated, as described in Section 3.2. The orientations of the word-tags are set to the identity matrix, that is, $\mathbf{R}(0) = \mathbf{I}_0$ (i.e., indicating horizontal word-tags), and the positions of boundary and virtual bodies are determined according to the boundary contour and empty regions, respectively, as described in Section 3.3.2. The linear momentum $\mathbf{L}(0)$ and angular momentum $\mathbf{A}(0)$ of all the bodies are set to $\mathbf{0}$, meaning that all of the bodies are initially static. When the dynamics starts, an iterative solver is adopted to compute the total external forces $\mathbf{F}(t)$ and torques $\boldsymbol{\tau}(t)$, and then to update the current state vector $\mathbf{Y}(t)$ and the auxiliary terms in Eq. (9) (i.e., inertial tensor $\mathbf{I}(t)$, velocity $\mathbf{v}(t)$, and spinning vector $\boldsymbol{\omega}(t)$) for the calculation of the derivative of the state vector, that is, $\frac{d}{dt}\mathbf{Y}(t)$. The update of the state vector is exclusive of the boundary and virtual bodies because they are static over time. This iterative process terminates when the differences between the velocities of bodies at the current step and the previous step are smaller than a specified threshold δ.

4 Results and Discussion

4.1 Properties of the Proposed Methods

The proposed method introduces several properties that demonstrate a potential for generating morphable word clouds. First, the generated word clouds are inherently overlap-free because of rigid body dynamics. Each word-tag is viewed as a rigid body, and the use of collision detection and contacting constraints leads to an overlap-free layout. As shown in Fig. 10, overlapping occurs in a word-tag layout is solved by using the rigid-body dynamics with the contacting constraints. Second, with the use of the orientation and position constraints, the proposed method offers several fundamental editing functions, including fixing a word-tag in a specific position (Fig. 9), changing the position and orientation of a word-tag, and arranging word-tags in a specific direction (Fig. 7). These functions result in flexible editing of time-varying word clouds. Third, by using boundary constraints, the proposed method can arrange a time-varying word cloud in a specific shape, as shown in Fig. 11. In addition, similar to [13], our method can pack word-tags as compactly as possible. A compact layout is achieved by disabling the uniform and boundary constraints, and setting a virtual body with strong attracting forces in the center of the word cloud. This virtual body can force the word-tags to move toward the center under the contacting constraints. Fourth, the temporal coherence of word-tags can be maintained because of the initial positions and temporal coherence constraints of word-tags. As shown in Fig. 11, the temporal coherence of the word-tag "Apple" is maintained in the motion sequence.

Algorithm. The Pseudocode of Dynamics Process

Input: word-tags[N], tag-sizes, virtual bodies, and boundary bodies.
Output: the tag position $\mathbf{x}(t)$.

Procedure *RigidTagMotion(word-tags[N])*
// Initialization Step
For each body
$\mathbf{I}_{tag} = \sum_{i=1}^{N} m_i(\hat{\mathbf{r}}_i^T\hat{\mathbf{r}}_i\mathbf{I}_0 - \hat{\mathbf{r}}_i\hat{\mathbf{r}}_i^T)$;
$M \leftarrow \sum_{i=1}^{N} m_i$;
// Initialize all tag positions, orientations, linear and
// angular momentums.
Initialize the state vector $\mathbf{Y}(0) = (\mathbf{x}(0), \mathbf{R}(0), \mathbf{L}(0), \mathbf{A}(0))$;
// Motion Step
Repeat
For each body $\in$ *word-tags[N]*
// Update the external forces $\mathbf{F}(t)$ and torques $\boldsymbol{\tau}(t)$
$\mathbf{F}(t) \leftarrow \sum_i \mathbf{F}^i_{uniform} + \sum_j \mathbf{F}^j_{temporal}$;
$\boldsymbol{\tau}(t) \leftarrow \sum_i r_i \times \mathbf{F}^i_{uniform} + \sum_j r_j \times \mathbf{F}^j_{temporal}$;
// Update the current state vector $\mathbf{Y}(t)$
$\mathbf{x}(t) \leftarrow \mathbf{x}(t-1) + \triangle t\mathbf{v}(t-1)$;
$\mathbf{R}(t) \leftarrow \mathbf{R}(t-1) + \triangle t(\boldsymbol{\omega}(t-1)\mathbf{R}(t-1))$;
$\mathbf{L}(t) \leftarrow \mathbf{L}(t-1) + \triangle t\mathbf{F}(t-1)$;
$\mathbf{A}(t) \leftarrow \mathbf{A}(t-1) + \triangle t\boldsymbol{\tau}(t-1)$;
// Update the auxiliary quantities in Eq. (9)
$\mathbf{v}(t) = \mathbf{F}(t)/M$;
$\mathbf{I}(t) = \mathbf{R}(t)\mathbf{I}_{tag}\mathbf{R}(t)^T$;
$\boldsymbol{\omega}(t) = \mathbf{I}(t)^{-1}\mathbf{A}(t)$;
// Handle the colliding contact problem
CollidingContact();
Until $|\mathbf{v}(t) - \mathbf{v}(t-1)| < \delta$
Output $\mathbf{x}(t)$;

4.2 Experimental Results

The proposed method was implemented by Java, and all experiments were evaluated on a PC with a 3.6 GHz CPU and 4 GB memory. The processes of document analysis, shape interpolation, and layout initialization were performed in the preprocessing. As for the dynamic word-tag arrangement, our method takes averagely 5.02 milliseconds to arrange a dataset with 100 word-tags. Therefore, our method takes 7.54 seconds to generate a word cloud morphing that contains 1,500 frames (about 50 seconds of animation). The performance of our algorithm depends on the

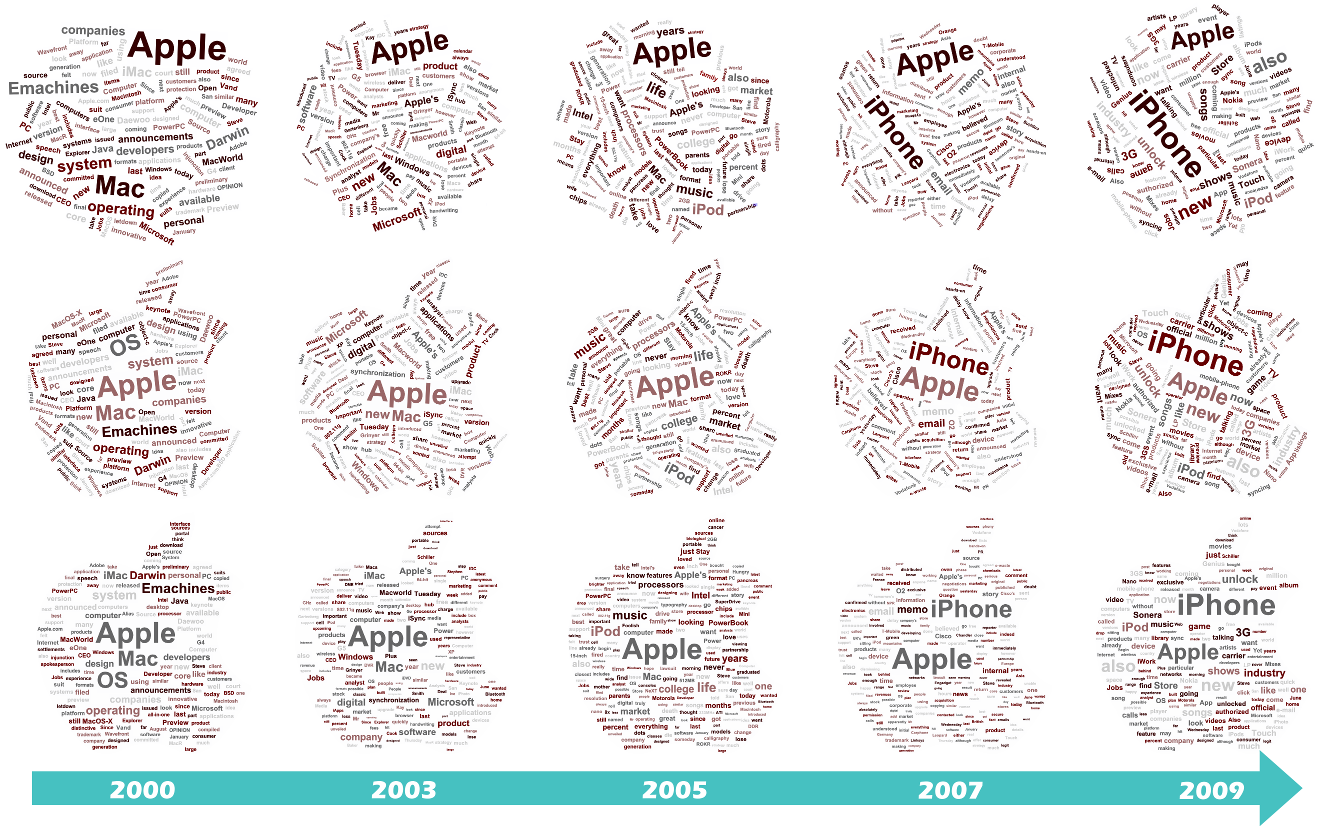

Fig. 11. Morphable word cloud results. Top: arranging the time-varying word cloud as compactly as possible; middle: arranging the time-varying word cloud in an apple shape; bottom: arranging word-tags in horizontal direction.

number of word-tags (W), the number of iterations in dynamics (I), and the number of frames in animation (F). The time complexity of our method is $O(IFWlogW)$. Fortunately, I and W can be regarded as constants of small values because these two numbers are generally much smaller than F. Therefore, the computational time increases approximately linearly with the number of frames.

To demonstrate the feasibility of the proposed method, various multi-temporal word-tags were tested. Some representative cases are displayed in Figs. 1, 11, and 12, and the others are attached in accompanying documents. In the experiment shown in Fig. 11, a collection of articles related to Apple Inc. from 2000 to 2009, downloaded from the apple-history website,[1] is tested. From the results, we can see that the word-tag "iPhone" appears in the fourth word cloud in 2007 because the first generation iPhone was released in 2007. This word-tag is enlarged after 2007 because of the increasing sales of iPhone. Similarly, the word-tag "Mac" is gradually shrunk after 2000 because of the decreasing sales of Macintosh. Compared with [5] that can arrange word-tags as compactly as possible, our method can also generate a compact word-tag arrangement while maintaining temporal coherence. In addition, our method can arrange word-tags in a specific shape, resulting in a pleasing and engaging visual representation of text documents.

In Figs. 1 and 12, the collections of articles related to human evolution (six million years ago to present), human life cycle (from infancy to late adulthood), pitching action, and frog life cycle are tested. The sequences of boundary contours are extracted and used as boundary constraints in rigid body dynamics. Therefore, the word-tags are arranged in shape sequences, and the spatial-temporal changes are presented in the motions and shapes of word clouds. These cases demonstrate the ability of our method to generate morphable word clouds for providing continuous and pleasing spatial-temporal visualization. The generated word clouds can potentially serve as a storytelling tool in exhibition. All the results were automatically generated using the default parameters. The maximal and minimal font sizes, that is, T_{max} and T_{min} in Eq. (1) are set to 100 and 10, respectively. The denseness of word-tags T_d is set to 80. These three parameters are tunable and are determined by users. If these parameters need to be determined automatically to balance space utilization and word readability, the automatic optimization process suggested by Liu et al. [27] can be performed.

5 User Study

A user study involving 58 participants, aged 20 to 45 years, was conducted to evaluate the proposed method. The 53 participants were college students in Tainan, Taiwan, and the others were college professors and artists. In the user study, we compared five word cloud representations, namely, Sparkclouds (SC) [3], structured parallel coordinate (SPC) [6], static word cloud (SWC), and the proposed morphable word cloud in a horizontal

1. http://www.apple-history.com/

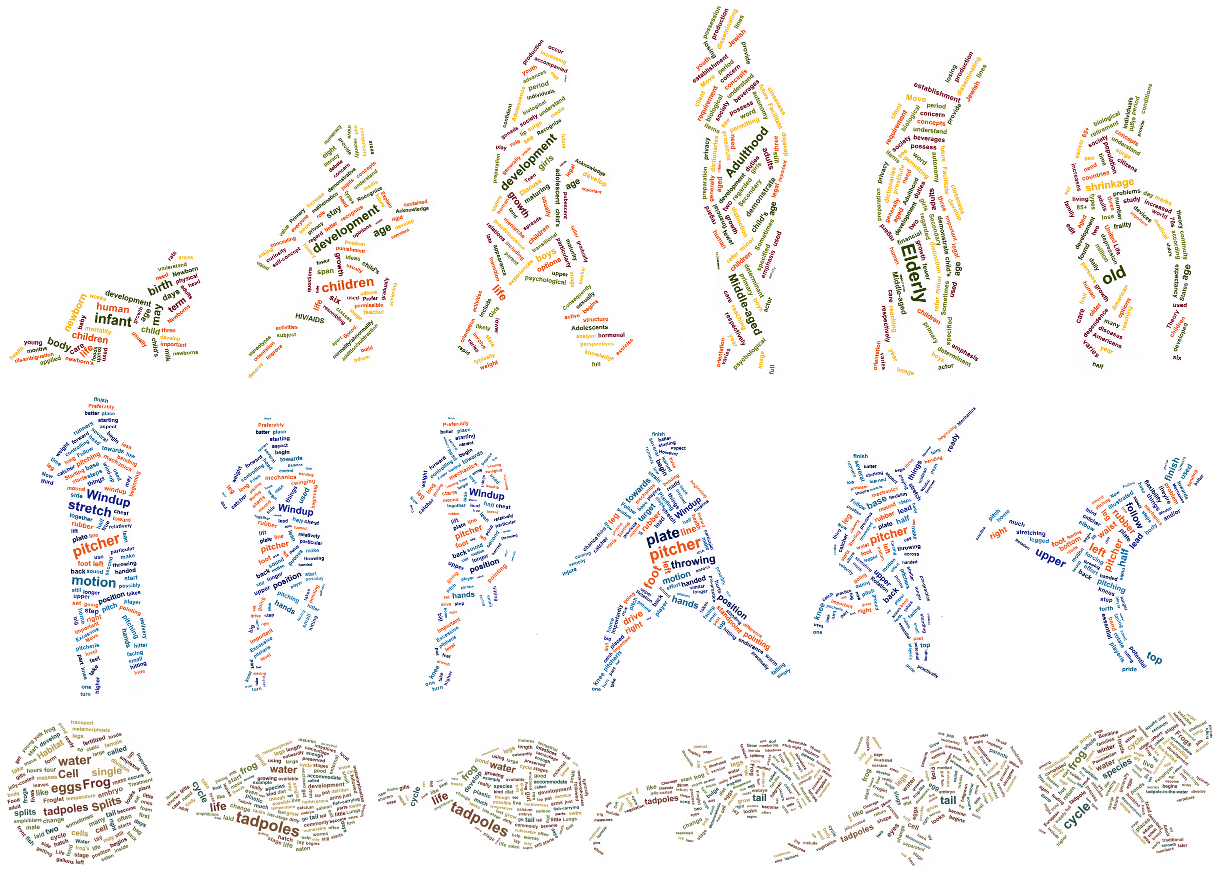

Fig. 12. Word cloud morphing results. From top to bottom: word cloud morphings that illustrate the stages of the human life cycle (from infancy to late adulthood), the pitching action, and the frog life cycle.

arrangement (MWC-h) and an arbitrary arrangement (MWC-a). SC and SPC are recent time-varying word cloud methods focused on trend visualization. SC integrates sparklines into a word cloud to convey trends between multiple word clouds. The SPC visualizes a time-varying document by utilizing the graphical elements of parallel coordinates. Each column in the parallel coordinates represents a list of word-tags appearing at a time point. The open sources of SC[2] and SPC[3] in the WWW were used in the comparison. The static word clouds were generated using our method without shape transition. Visual comparisons of SC, SPC, SWC, and our results are shown in Figs. 12 and 13.

5.1 Study Design

The word clouds from these five representations are compared using three predefined tasks, including the tasks of readability, theme representation, and trend visualization, and one questionnaire about word cloud characteristics. The first task is performed to test the readability of word clouds while the second and third tasks focus on understanding the abilities of theme representation and trend visualization of word clouds. These three tasks are summarized in Table 1. In the first task, participants are shown a word cloud and are asked to memorize the word-tags inside the word cloud in 40 seconds. They are then instructed to select two words appearing in the word clouds from the set of 10 words; only two out of the 10 options are correct. In the second task, the participants are asked to select the best theme title for the word cloud, and they are given five theme titles to choose from. In the third task, the participants are asked to select the fittest trend curve for a specific word as quickly as possible. Similarly, they are given five trend curves to choose from. In the questionnaire, the participants are asked to select one or more characteristics of the word cloud. They are given six options, namely, aesthetic, practical, innovative, interesting, engaging, and informative.

A within-subjects design (five representations $\times$ three tasks) is adopted in this study. Hence, each participant performs all tasks and uses all the visualizations. Five datasets, namely, human evolution, history of dinosaur, frog life cycle, pitching action, and human life cycle, are used in the user study. The representations and tested data are randomly arranged to avoid learning effects. One-way ANOVA is performed on the task completion times. The study begins with a 10 min. introduction to the word cloud, the user study, and the interface (including the demonstrations of the zooming and pausing functions for the morphable word clouds). The participants are asked to answer the question of the first task after 40 seconds of observation and answer the questions of the second and third tasks as quickly as possible without sacrificing accuracy. The response times and accuracy rates are recorded. At the end

2. Open source of Sparkclouds: http://www.cg.tuwien.ac.at/courses/InfoVis/HallOfFame/2012/Gruppe04/Homepage/index.html

3. Source code of structured parallel coordinates: http://webfolder.eurac.edu/EURAC/Commul/linfovis/StructuredParCoords/examples/parallelTagClouds.html

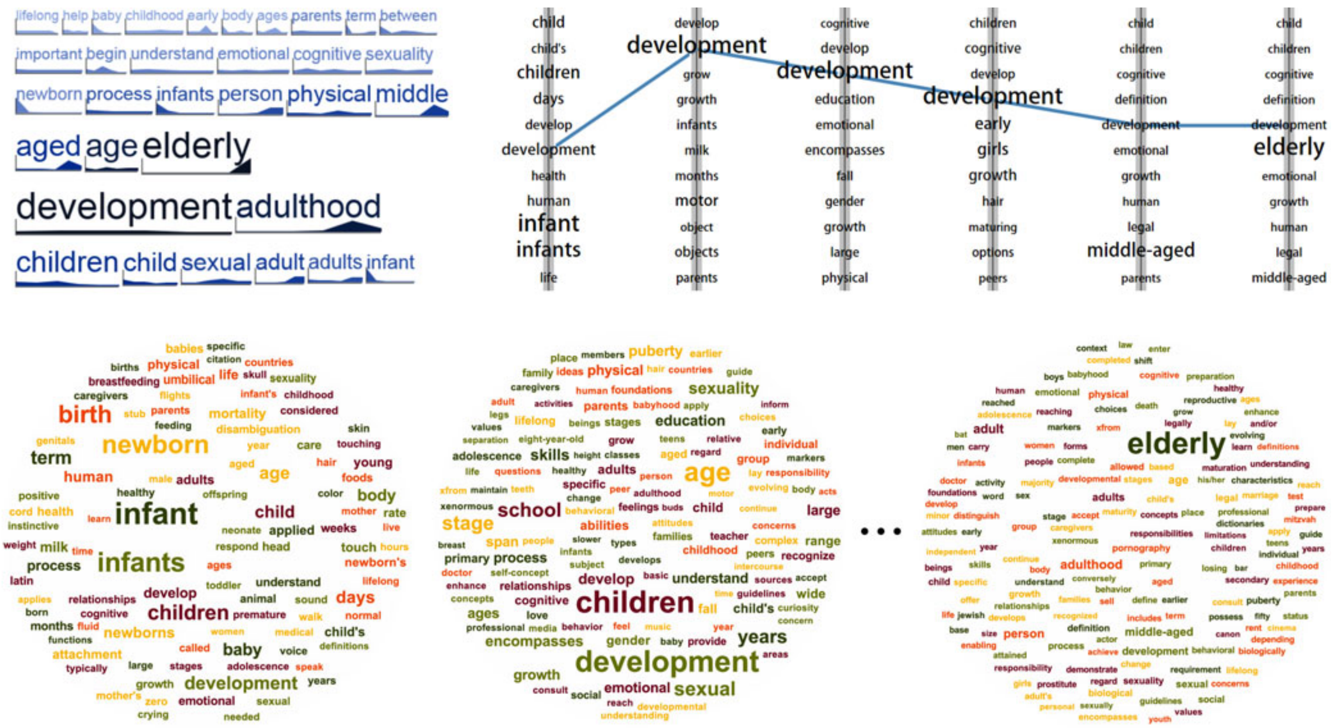

Fig. 13. Results of SC [3] (top-left), SPC [6] (top-right), and static word cloud (bottom).

of each task, the participants are allowed to provide their comments on the task and word cloud representation, as well as the reasons behind their choices. The user study lasts approximately 30 min. for each participant.

5.2 Study Results

The selection accuracy and task completion times for tasks 1-3 are shown in Figs. 14, 15, and 16. The results show that SC has the best selection accuracy and task completion time for the readability and trend visualization tasks, while MWC-h has the best selection accuracy and task completion time for the theme representation task. In addition, the analysis of variance (ANOVA) indicates that the task completion times of the theme representation differ significantly across the five visualization results, $F(4, 285) = 7.2, p < .001$. These results indicate that SPC and SC have high readability and are effective for trend visualization while our method is suitable for theme representation. In the questionnaire, the study result in Fig. 16 shows that MWC-h and MWC-a receive over 35 votes from 58 participants for the aesthetic, interesting, and engaging options. This result indicates that most of the participants agree that our results are more pleasing and attractive than those of the other representations. We can thus say that our goal of providing an engaging representation has been achieved. Besides, most of the participants prefer our results to the static word clouds. The numbers of votes on the aesthetic, interesting, and engaging options significantly increase by 25, 59.5, and 49.1 percent, respectively.

In this user study, we receive several positive comments from the participants about our results, such as "They were interesting and pleasing to the eye" and "I like the animation. I can catch the point from the animation". However, we also receive a few negative comments such as "The animating word cloud is interesting. I have not seen that before. But, the rotating word-tags distract me from reading". From this feedback, we find that the generated word clouds are interesting. However, the readability of the word clouds decreases because of the rotated word-tags.

TABLE 1
User Study Tasks

ID	Task type	Question type	Task description
T1	Readability	Multiple choice	Select two words appearing in the word clouds from ten words after observing a word cloud for 40 seconds.
T2	Theme representation	Single choice	Select the theme represented by the word cloud as quickly as you can.
T3	Trend visualization	Single choice	Select the temporal trend of a specific word in a word cloud as quickly as you can.

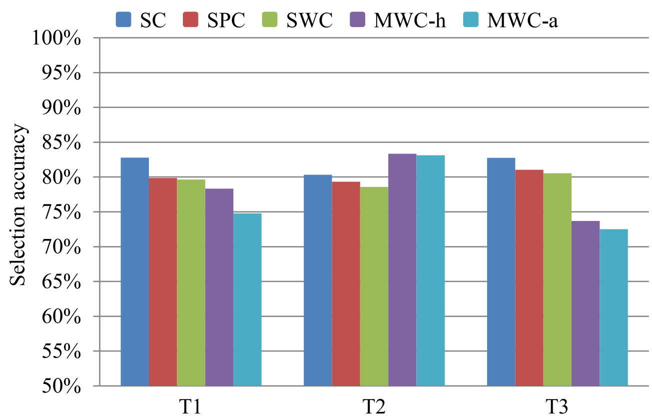

Fig. 14. Selection accuracy for the tasks of readability (T1), theme representation (T2), and trend visualization (T3).

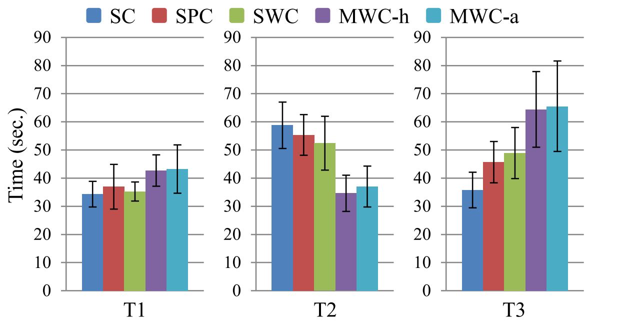

Fig. 15. Mean task completion time. The *y*-axis represents the task completion time in sections, and the *x*-axis denotes the five word cloud representations.

To alleviate this problem, the word-tags can be arranged in a horizontal direction, and the generated frames of the word cloud sequence can be displayed side by side manner instead of in a continuous manner.

6 Conclusions

A method to generate morphable word clouds is presented. Word-tag arrangement by using rigid body dynamics with the geometric, aesthetic, and temporal coherence constraints offers several advantages, including word-tag overlapping is inherently free, flexible editing of time-varying word clouds is allowed, arranging word-tags in a compact layout or a shape sequence is allowed, and temporal coherence of word-tags is maintained. The experimental results demonstrate the feasibility and flexibility of our method in generating a time-varying and morphable word cloud. In addition, the study results indicate that our method can provide an aesthetically pleasing and engaging visualization of time-varying data. These properties make our results suitable to serve as a digital storytelling tool.

Our method has the following limitations. Each word-tag is viewed as a rigid body in the dynamics. Thus, a word-tag cannot be arranged inside another word-tag. This problem can be solved by using a compact polygon of arbitrary genus to represent a word-tag (e.g., using a doughnut-shaped polygon to represent the letter "O") in collision detection and contact calculation. However, this approach is computational inefficiency. Another limitation is that our method cannot well handle a dumbbell-like shape with very thin connector, as shown in Fig. 17, if user-defined constraints are disallowed. In this extreme

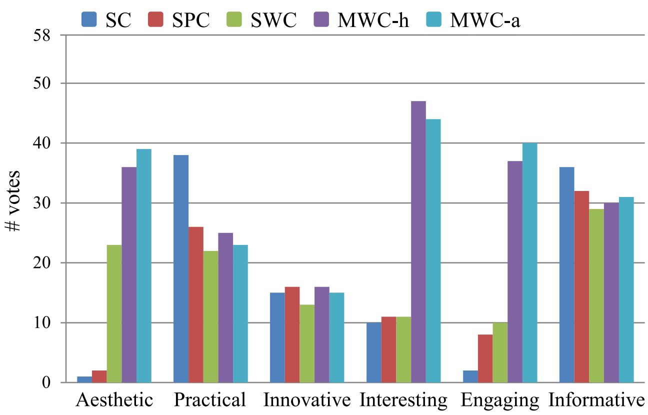

Fig. 16. Results of the questionnaire study.

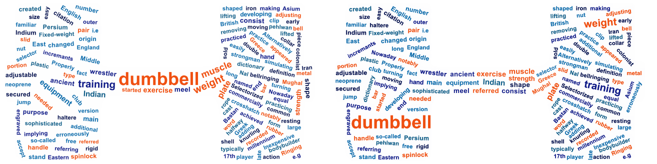

Fig. 17. Blocking problem. The blocking problem (left) can be solved by fixing the position of the word-tag "dumbbell" (right).

case, a large word-tag may block other word-tags from reaching their optimal positions. A possible solution to this problem is initially assigning a small font size to the large and blocking word-tags and using position and orientation constraints to fix them in specified positions during the dynamics iteration. For instance, in Fig. 17, the blocking problem occurs because of the word-tag "dumbbell". This problem can be solved by constraining the position of this word-tag. Besides, the generated word clouds cannot represent the changes in the words from a streaming data source. A possible solution to this problem is temporally partitioning the streaming data into several sub-data, and the sub-data are displayed using our method.

In the near future, we plan to develop a system for text art generation. This system can be achieved by integrating vector flow into the word-tag arrangement and depicting the temporal changes by dropping shadow/glow effect. We also plan to develop a user interface to edit time-varying word clouds, and plan to improve the computational performance by using a hierarchical structure in word-tag arrangements.

Acknowledgments

The authors would like to thank the anonymous reviewers for their valuable comments and suggestions to improve the manuscript. The authors also appreciate Mr. Yen-Ting Li and Mr. Chun-Yun Chiu for helping on the user study. This research was supported in part by the Headquarters of University Advancement at the National Cheng Kung University, and was supported in part by the Ministry of Science and Technology (contracts MOST-102-2420-H-004-045-MY3, MOST-103-2221-E-004-008, MOST-104-2221-E-006-044-MY3, and MOST-103-2221-E-006-106-MY3), Taiwan.

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