CLOTH COVERING AND APPLICATION TO FEATURE EXTRACTION FOR SCRIPT IDENTIFICATION

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Abstract: This paper proposes a concept and algorithm of cloth covering. It is a physically-based model which simulates computationally a shape of cloth covering some objects. It has one scale parameter which controls the degree of suppressing fine-scale structures. To show viability of the proposed cloth covering, this paper performed an experiment of script recognition. The results of comparing accuracies of feature extraction using Gaussian and cloth covering showed that the cloth covering is superior to Gaussian.

1 INTRODUCTION

The multi-scale representation of signals or images is important issue in various research communities such as signal processing, computer vision, and pattern recognition (Lindeberg, 1994). The scale-space theory supported by multi-scale representation methods is motivated from biological vision and physics. The most popular method is using Gaussian kernel as a smoothing operator. The Gaussian has one scale parameter which controls the degree of suppressing fine-scale structures in given signals or images. The scale-space theory has many applications which could benefit from scale-invariance property, such as feature extraction (e.g., SIFT (Lowe, 2004)), edge detection (Yuille et al., 1986) (Lindeberg, 1998), and interest feature point detection (Mikolajczyk et al., 2004).

This paper proposes a novel model which computationally simulates the physical phenomenon of cloth covering. The initial cloth on ground level is lifted under predefined rules to cover the objects until it reaches a stable state. In this process, the cloth is modeled as a list of balls connected by rubber band.

Since the objects covered by the cloth lose their details and appear only in their outlines, basic effect of the cloth covering operation is suppressing fine-scale structures of given signals or images. In other words, the operation transforms microscopic structure into macroscopic one. It has one scale parameter which controls the degree of suppressing fine-scale structures.

To show viability of the proposed cloth covering, this paper performed an experiment of script recognition. Text line images written in three different scripts were used by the experiment. Coefficients taken from Fourier transforms of profile and projection of line images were used as features. For feature extraction, Gaussian and cloth covering were applied to the raw profile and projection signals. The results of comparing their accuracies showed that the cloth covering is superior to Gaussian.

Section 2 presents principle and algorithm of the cloth covering. Section 3 presents experiments done using script recognition problem. Section 4 concludes the paper.

2 PRINCIPLES & ALGORITHMS

As Figure 1 shows, the cloth is modeled as a list of cloth elements connected by elastic material. The elastic material is an object with elasticity such as rubber band or spring. This paper calls it as *rubber band*. The cloth element is an object with weight. This paper calls it as *ball*. The paper assumes all the balls have the same weight and the rubber band is weightless. It also assumes that the length of rubber band is proportional to the weight given to the rubber band, i.e., proportional to the number of balls hung from the rubber band.

Figure 1: The cloth is modeled by a list of balls connected by rubber band.

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2.1 Dynamics

Assume that two balls with weight m are connected by a rubber band with elasticity coefficient k. When a ball is lifted up high enough that the other ball is hung in the air, the resulting length of rubber band (denoted by x) is proportional to the force gived on the rubber band. We can formulate $f=kx$ by Hook's law. Since the only force on the rubber band is the weight of hanging ball, we can write $f=mg$ where g is the gravitational acceleration. So the length of rubber band is $x=mg/k$ (Halliday, 2008).

Let's extend the situation to one where four balls are connected as in Figure 2(a). In this situation, the length of rubber band 3 is equal to mg/k. However since two balls are hung from rubber band 2, the length of rubber band 2 is $2mg/k$. Similarly the length of rubber band 1 is $3mg/k$.

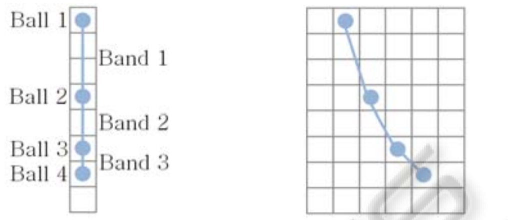
Let's generalize the phenomenon. When n balls are hung from a rubber band, the length of the rubber band is nmg/k. Since m, g, k are constant, let's replace $k/(mg)$ by τ. Now the length of rubber band from which n balls are hung can be written by Equation (1).

$$x=\frac{1}{\tau}n \qquad (1)$$

In Equation (1), τ is the parameter which controls stiffness of the cloth. The larger the τ is, the stiffer the cloth is. On the contrary, as τ becomes smaller, the cloth becomes smooth and the final shape is similar to the original signal. We call τ as *stiffness coefficient*.

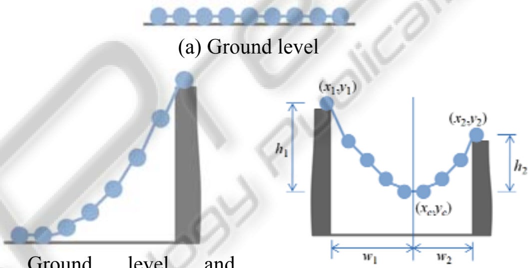
In order to define the cloth covering operation over 1-dimensional signal, let's change the situation of Figure 2(a) to Figure 2(b). In the new situation, four balls are not located on the same column but on adjacent columns. Though physically the length of rubber band should be calculated considering vertical and horizontal forces, this paper considers only the vertical direction for computational simplicity. So Equation (1) can be applied to the situation of Figure 2(b).

Figure 3 illustrates three primitive situations which algorithm of the cloth covering should deal with. Figure 3(a) is the case where the signal is ground level. In this case, the cloth is on ground level. Figure 3(b) is one where one side is ground level and the other side is on top of supporting bar. In this case, the cloth shape can be calculated using Equation (1). Figure 3(c) shows the case where both sides are on top of supporting bars. Since in this case the cloth can't be calculated simply by using Equation (1), we divide the rubber band into two parts. We assume that two parts are independent, i.e., they do not influence on the resulting shape each other. We take the lowest ball as the point where the rubber band is split into two parts. After splitting the rubber band, Equation (1) can be applied to each of two parts.



(a) Balls at the same column (b) Balls at neighbor columns

Figure 2: Four balls hung from top.



(a) Ground level

(b) Ground level and supporting bar (c) Two supporting bars

Figure 3: Three primitive situations.

Now we will explain the procedure to find out the lowest ball for the case of Figure 3(c). Let the lowest point to be (x_c,y_c) and the coordinates of top of supporting bars to be (x_1,x_1) and (x_2,y_2). Then the height can be written as $h_1=y_1-y_c$ and $h_2=y_2-y_c$. And the width are $w_1=x_c-x_1$ and $w_2=x_2-x_c$. The values of h_1 and h_2 can be calculated by summing Equation (1) as shown in Equation (2).

$$h_1=\frac{1}{\tau}\sum_{i=1}^{w_1} i \;,\quad h_2=\frac{1}{\tau}\sum_{i=1}^{w_2} i \qquad (2)$$

Since the left and right parts are connected at the lowest point, the equation, $y_c=y_1-h_1=y_2-h_2$ holds. Rearranging the equation, we get Equation (3).

$$x_c=\frac{2\tau(y_1-y_2)-(x_1^{\,2}-x_2^{\,2}-x_1-x_2)}{-2(x_1-x_2-1)} \qquad (3)$$

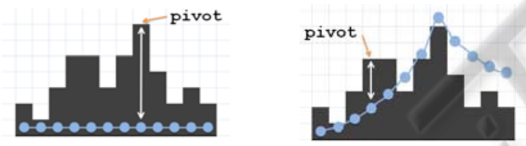
2.2 Algorithm

In the situations of Figures 3, balls at the ends are fixed on ground or on top of supporting bars. In other words, we know two contact points where the ball is contact with signal level. However, in the initial state, no contact point is known. This section explains the algorithm which starts with the initial state and ends with the final cloth shape.

Figure 4(a) shows the initial state which the algorithm starts with. In this state, the algorithm attempts to decide a ball which is doomed to contact with cloth. The point is called as pivot point. The criterion to choose the pivot point is maximizing the height difference between current cloth and the input signal. The pivot point is indicated in figure 4(a).

The cloth is lifted at the pivot so that the cloth is contact with the signal level at the pivot as Figure 4(b) shows. Then the cloth is split into two parts at the pivot, and two parts proceed the same procedure independently. Figure 4(b) indicates the new pivot for the left part.

The algorithm can be written in a recursive procedure in Algorithm 1. The algorithm starts with ground level cloth of C[*i*]=0, *i*=0,*n*-1. The recursive function Covering(*p*,*q*) finds out pivot point in the range [*p*,*q*], and lifts up the current cloth to the signal level at pivot point. Then it computes new cloth using the process of Section 2.1 and calls recursively Covering() for each of left and right parts.



(a) (b)

Figure 4: Algorithm for cloth covering (recursively splitting at pivots).

Algorithm 1: 1-dimensional cloth covering

```
Input: D[0,n-1]   //input signal
Output: C[0, n-1] // cloth shape

1. C[i] = 0, 0≤i≤n-1
2. Covering(0, n-1);

Covering(p, q)
{
    if(p == q) return;
    pivot = argmax_{p≤k≤q}(D[k] – C[k]);
    if(D[pivot] – C[pivot] ≤ 0) return;
    C[pivot] = D[pivot];

    Physics(p, pivot);
    Covering(p, pivot);

    Physics(pivot, q);
    Covering(pivot, q);
}
Physics(p, q)
{
    update cloth shape in the range [p,q] using
dynamics in Section 2.1;
}
```

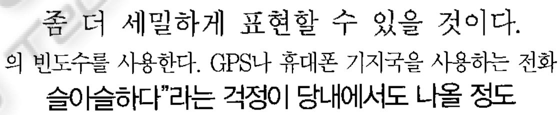
The average and worst case time complexity of Algorithm 1 is O(*n*log*n*) and O(n^2) where *n* is the number of balls, i.e., length of signal.

3 APPLICATION TO SCRIPT IDENTIFICATION

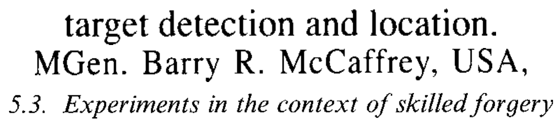
The script identification is a sub problem of OCR (Optical Character Recognition) (Marinai, 2008). Figure 6 shows text line images written in different scripts, Korean, Latin, and Chinese. In conventional researches, Fourier coefficients extracted from profile and projection of line images were used as feature set (Ghosh et al., 2011) (Pal et al., 2002). Some literatures applied Gaussian filter to profile and projection signals before Fourier transform in order to suppress the details of signals. The aim of this section is to compare the proposed cloth covering with Gaussian filter in terms of feature's discriminating power.

3.1 Feature Extraction

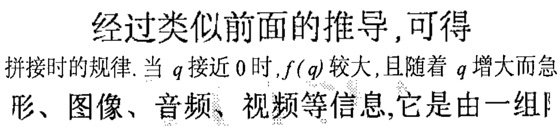
One of the popularly used features is profile and projection. Figure 6(b) presents top profile, bottom profile, and projection. The Fourier coefficients taken from Fourier transform of profile and projection signals were used as feature vectors by



(a) Korean



(b) Latin



(c) Chinese

Figure 5: Text line images written in three scripts.

the classifier (Ghosh et al., 2011) (Pal et al., 2002). This paper calls this feature vector as Raw-Fourier.

As we can observe in Figure 6(b), the raw profile and projection conveys detail shapes of input line images. We may think of using coarse version of profile and projection with the hope of improving discriminating power of the feature vector. Figures 6(c) and 6(d) show the Gaussian-smoothed profile

Table 1: Size of data sets.

	Korean	Latin	Chinese
number of documents	69	44	37
number of text lines	2874	2818	1337

Table 2: Recognition accuracies.

Feature extraction methods		Number of features				
		150	120	90	60	30
Raw-Fourier		97.67	96.90	96.50	94.28	89.19
Gaussian-Fourier	$\sigma = 1$	97.71	97.03	96.64	94.57	89.44
	$\sigma = 2$	97.68	97.20	96.57	94.58	89.50
	$\sigma = 3$	97.81	97.37	96.63	94.58	89.60
	$\sigma = 4$	97.62	97.48	96.76	94.76	89.66
	$\sigma = 5$	97.52	97.37	96.69	94.58	89.74
Covering-Fourier	$\tau = 1$	97.55	97.52	97.27	95.72	93.10
	$\tau = 5$	98.41	98.26	98.01	97.52	**95.58**
	$\tau = 9$	**98.79**	98.72	98.46	97.70	95.55
	$\tau = 13$	98.75	98.75	**98.73**	97.72	95.08
	$\tau = 17$	98.71	**98.78**	98.73	**97.79**	94.66
	$\tau = 21$	98.71	98.72	98.62	97.52	94.05

and projection. Fourier coefficients taken from Fourier transform of Gaussian-smoothed profile and projection signals are used as feature vector. The feature vector is called as Gaussian-Fourier(σ) where σ represents standard deviation of Gaussian function being used.

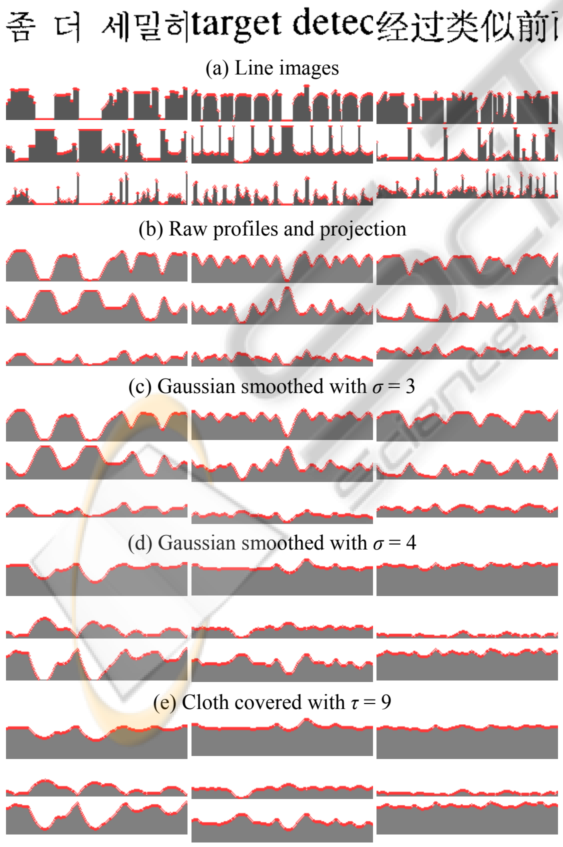


Figure 6: Top profile, bottom profile, and projection.

The cloth covering can also be used to suppress the details. The result of cloth covering over the top (bottom) of line image is called as *top* (*bottom*) *cloth profile*. The difference of top and bottom profiles is called as *cloth projection*. Figures 6(e) and 6(f) depict the cloth profile and cloth projection. Fourier coefficients taken from Fourier transform of cloth profile and cloth projection signals are used as feature vector and it is called as Covering-Fourier(τ) where τ represents stiffness coefficient.

3.2 Experimental Results and Analysis

The data sets used by experiments have been collected from various documents, including technical papers, magazines, and books. The used scripts are Korean, Latin, and Chinese. The images were scanned in 300dpi. Table 1 shows size of data sets. For classification, we used SVM (Burges, 1998). In measuring recognition accuracy, we used 5-fold cross validation.

Table 2 presents recognition accuracy measured for three types of feature vector, Raw-Fourier, Gaussian-Fourier(σ), and Covering-Fourier(τ). To get finer analysis, we took different number of coefficients from Fourier transform. When we took 50 coefficients from one signal, total number of features is 150 since we used three signals, top profile, bottom profile, and projection.

Comparing raw signals and smoothed signals, the table makes sure that both Gaussian and cloth covering are superior to raw signals. We argue that using the detail shapes as they are does not provide good discriminating power of features. In each column, the best accuracy is visually emphasized using bold typeface. The cloth covering won every column. The cloth covering was better than Gaussian by more than about 1%. We recommend 9 or 13 for the scale parameter τ.

The cloth covering produced similar accuracies for the feature vector size of 90~150. On the contrary, Raw-Fourier and Gaussian-Fourier decreases rapidly as number of features decreases.

4 CONCLUSIONS

This paper proposed a novel multi-scale method called cloth covering. The paper presented algorithms for 1-D cloth covering. Using script recognition experiments, we showed viability of the cloth covering.

There are a number of futures of the cloth covering. Firstly, mathematical properties are worth of studying. Comparison with Gaussian and mathematical morphology could guide the study. Secondly, application areas in which the cloth covering competes with or superior to conventional method should be identified. As a specific area, keypoint detection for SIFT is being studied by authors. The conventional SIFT uses DOG (Difference of Gaussian). Our concern is to test the performance when we replace DOG with DOC (Difference of Cloth covering). Thirdly, algorithms for n-dimensional signals should be developed. The priority is on developing algorithm for 2-D images.

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