Appearance Similarity Index for Medicinal Ampoule Labels

Masaomi Kimura[1], Yutaroh Furukawa[1], Akira Kojo[1], Hirotsugu Ishida[2], Keita Nabeta[2], Michiko Ohkura[1], and Fumito Tsuchiya[3]

[1]Shibaura Institute of Technology,
3-7-5 Toyosu, Koto Ward, Tokyo 135-8548, Japan
{masaomi,ohkura}@shibaura-it.ac.jp
[2]Graduate School of Technology, Shibaura Institute of Technology,
3-7-5 Toyosu, Koto Ward, Tokyo 135-8548, Japan
{m110013,m709102}@shibaura-it.ac.jp
[3]International University of Health and Welfare,
2800-1 Kitakanemaru, Ohdawara City, Tochigi 324-8501, Japan
ftsuchiya@iuhw.ac.jp

Abstract. Since there are many ampoule injection medicines, it is important to make their labels easily distinguishable because confusing labels may lead to fatal accidents caused by administering the wrong medicine by mistake. In this paper, we utilize Fourier series expansion and wavelet transformation to extract the characteristics in labels and propose an index to measure similarity that we feel toward ampoule labels to prevent confusion in label designs. We also discuss a way of parameterizing colors.

Keywords: Medicinal safety, Ampoule labels, Fourier analysis, Wavelet analysis.

1 Introduction

Since there are many ampoule injection medicines, it is important to make their labels easily distinguishable because confusing labels may lead to fatal accidents caused by administering the wrong medicine by mistake. However, labels tend to be similar because they are small and there is little freedom in their design elements. It is necessary to define an appearance similarity index and to warn authorities against approving labels that may cause confusion.

The confusion over labels is similar to the problem of medicines having similar names, since this can also result in accidents caused by administering the wrong medicine by mistake. Tsuchiya et al. [1] proposed indices that measure the similarity of medicine names, such as the cosine value, which measures the angle between vectors whose elements denote the frequency of each letter. He also developed a similar name search system based on the indices. The system is actually used to prevent approval of medicine that has a similar name to those of existing medicines. However, there have been no studies on evaluating the visual similarities of packages, especially ampoules, of injection medicines. Nabeta and Imai et al. [2] proposed a

J.A. Jacko (Ed.): Human-Computer Interaction, Part I, HCII 2011, LNCS 6761, pp. 588–597, 2011.

similarity index that takes account of the similarity of letters appearing in medicine names.

Although the color and material of the container part can contribute to their similarity, in this paper, we focus on the similarity of ampoule labels because there is less variety in the color and material of container parts than labels and because how to measure similarity that we feel toward ampoule labels has not been clarified.

In order to design a similarity index for ampoule labels, we discuss how to extract data that contain information of their characteristics. In this paper, we introduce two ways of extracting such data: Fourier series expansion and wavelet transformation.

Fourier series expansion is useful for finding characteristics of periodic functions. Since the cross-section of labels forms a circle, the distribution of colors on labels can be regarded as an angular distribution function, which is periodic. Namely, if you deal with the components obtained by Fourier series expansion, it is automatically guaranteed that the original data is periodical. Therefore, we do not directly treat the original color distribution but the Fourier coefficients as the fundamental characteristic values to represent the angular color distribution of labels.

We also introduce analysis that utilizes (discrete) wavelet transformation[3] instead of Fourier series decomposition because we can feel similarity of not only the whole part of each label but also the part that is within the range of view. Although Fourier series decomposition provides us with the characteristics data of the whole label, wavelet transformation shows components of the localized 'wave' (wavelet) in the target function. We expect that the similarity of the components corresponds to similarity in the range of view.

We also discuss a way of parameterizing colors. Red, Green and Blue (RGB) are the most common color space. In this paper, we show that labels that have a wide white area in the background tend to have higher similarity values to any other labels. (Note that most labels have a white background.) We also adopt other color spaces, L*a*b* in order to decompose the lightness elements from the color space.

Based on these findings, we propose an appearance similarity index of labels. We regard the subset of the coefficient series obtained from Fourier analysis or wavelet analysis as a vector, and calculate cosine values that measure the angles between each pair of such vectors.

We evaluate our index by applying it to realistic ampoule labels. We calculate the values of our index and compare them with the answers of questionnaires asking the extent of similarity.

2 Methods

2.1 The Method Based on Fourier Series Expansion

In general, we utilize Fourier series expansion,

$$f(\theta) = \frac{a_0}{2} + \sum_{n=1}^{\infty}(a_n \sin n\theta + a_{-n} \cos n\theta) \tag{1}$$

in order to find the characteristics of periodic functions. In this study, we can regard the distribution of colors on ampoule labels as an angular distribution function along the cross-section of ampoules. The function is periodic since the cross-section of ampoules is a circle. Based on this consideration, we treat not the original color distribution but the Fourier coefficients as the fundamental data.

Let us parameterize each pixel of a label by a set of values (τ, θ), where θ denotes the angle measured along the edge of a cross-section of an ampoule and denotes the coordinate that is along the axial direction of the ampoule. Let R_θ^τ, G_θ^τ, B_θ^τ denote the color component values of red, green, blue respectively at the pixel (τ, θ). If we apply Fourier series decomposition to them, we find that

$$\begin{pmatrix} R_\theta^\tau \\ G_\theta^\tau \\ B_\theta^\tau \end{pmatrix} = \begin{pmatrix} r_0^\tau \\ g_0^\tau \\ b_0^\tau \end{pmatrix} + \sum_{n=1}^{\infty} \left\{ \begin{pmatrix} r_n^\tau \\ g_n^\tau \\ b_n^\tau \end{pmatrix} \cos n\theta + \begin{pmatrix} r_{-n}^\tau \\ g_{-n}^\tau \\ b_{-n}^\tau \end{pmatrix} \sin n\theta \right\}. \tag{2}$$

We deal with the first term and the other terms separately because the first term is a set of the mean values of each color and the other terms contain information of the extent of variation from the mean values of each color.

From now on, we assume that people feel similarity of labels based on the color and the display design (w/o color) printed on labels.

As for the mean value components, the corresponding spectral density at τ for each color is given by:

$$\frac{(r_0^\tau)^2}{2}, \frac{(g_0^\tau)^2}{2}, \frac{(b_0^\tau)^2}{2} \tag{3}$$

Since each of these represents the typical magnitude of each color at , we regard

$$v_\tau = \left(\frac{(r_0^\tau)^2}{2}, \frac{(g_0^\tau)^2}{2}, \frac{(b_0^\tau)^2}{2} \right) \tag{4}$$

as a vector whose direction indicates the tendency of color at τ . For the pair of drugs, we calculate the average similarity of colors as

$$sim^{color} = \frac{1}{m} \sum_{\tau} \frac{v_\tau \cdot v'_\tau}{\|v_\tau\| \|v'_\tau\|} \tag{5}$$

where m is the length (the number of pixels) of a label in the direction of τ .

Remember that $r_{\pm n}^\tau$, $g_{\pm n}^\tau$, $b_{\pm n}^\tau$ represent the magnitude of variation. We expect that these values contain information on display designs other than colors, such as lines, marks, letters and so forth. We assume that labels that have analogous patterns make us feel similarity even if their color is different. In order to extract the pattern information, we convert the color components R_θ^τ, G_θ^τ, B_θ^τ to grayscale, based on the approximate expression:

$$\mathrm{Gray}_\theta^\tau = \frac{2R_\theta^\tau + 4G_\theta^\tau + B_\theta^\tau}{7} \tag{6}$$

$$= \frac{2r_0^\tau + 4g_0^\tau + b_0^\tau}{7} + \sum_{n=1}^{\infty} \left(\frac{2r_n^\tau + 4g_n^\tau + b_n^\tau}{7} \sin n\theta + \frac{2r_{-n}^\tau + 4g_{-n}^\tau + b_{-n}^\tau}{7} \cos n\theta \right)$$

The components of their spectral density are given as:

$$q_n^\tau = \left(\frac{2r_n^\tau + 4g_n^\tau + b_n^\tau}{7}\right)^2 + \left(\frac{2r_{-n}^\tau + 4g_{-n}^\tau + b_{-n}^\tau}{7}\right)^2. \tag{7}$$

We regard a series of these as a vector and define the average similarity of display patterns as follows:

$$sim^{design} = \operatorname*{avg}_{\tau} \frac{\sum_n q_n^\tau q_n'^\tau}{\sqrt{\sum_n q_n^{\tau 2}}\sqrt{\sum_n q_n'^{\tau 2}}} \tag{8}$$

Now we have two similarity indices and find the way to unify these. We investigated the distributions of both similarity indices calculated for the pairs of 12 ampoule labels available in the market. The results are shown in Fig.1.

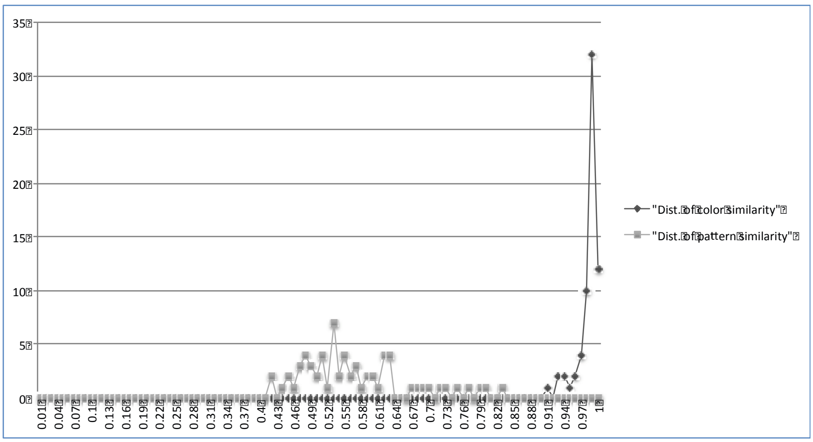

Fig. 1. Distributions of similarity indices

This figure tells us that the color similarity index shows unimodal distribution although the pattern similarity index shows multimodal distribution. This difference cannot be absorbed even by normalization. We focus on their rank to preserve the order of similarity. Let $rank_c$ and $rank_p$ denote the functions that return the rank counted in the ascendant order. The suffix c and p denotes the rank of color similarity index and pattern index, respectively. If N is the number of target ampoule labels, the maximum value of $rank$ is the number of the combinations of labels, namely $(N-1)/2$. Based on these considerations, we defined the normalized unified similarity as:

$$sim^f = 1 - \frac{rank_c(sim^{color}) + rank_p(sim^{design}) - 2}{N(N-1)} \tag{9}$$

2.2 The Method Based on Wavelet Transformation

We also introduce analysis that utilizes (discrete) wavelet transformation instead of Fourier series decomposition. This is under the assumption that we feel similarity of not only the whole part of each label but also the part that is within the range of view. Although Fourier series decomposition provides us with the characteristics data of the whole label, wavelet transformation shows the characteristic data of the parts covered by the localized ‘wave’ (wavelet) in the target function. We expect that the similarity of the parts corresponds to similarity in the range of view.

Let $h^{\tau}(x)$ be a target color component function at τ , where $x = \frac{\theta}{2\pi}$. Remember that the colors printed on the typical labels do not change gradationally. Because of this, we use Haar’s mother wavelet defined as

$$\psi(x) = \begin{cases} 1 & 0 < x \le \frac{1}{2}, \\ -1 & \frac{1}{2} < x \le 1, \\ 0 & otherwise. \end{cases} \tag{10}$$

In general, $h^{\tau}(x)$ can be decomposed as

$$h^{\tau}(x) = h^{\tau}_{J}(x) + \sum_{l=J}^{\infty} \sum_{k} \gamma^{\tau}_{l,k} \psi(2^{l} x - k). \tag{11}$$

where l is a scaling parameter and k denotes the displacement of a translation of Haar’s wavelet. The function $h^{\tau}_{J}(x)$ is the step function approximation of $h^{\tau}(x)$, each of whose intervals has the width 2^{-J}.

We assume that the display printed on each 1/4 part of a label can be recognized at a time, and each half of 1/4 part is overlapped. Taking account of these assumptions and the size of letters on the labels, we approximate $h^{\tau}(x)$ as

$$h^{\tau}(x) \approx h^{\tau}_{3}(x) + \textstyle\sum_{l=3}^{5} \sum_{k} \gamma^{\tau}_{l,k} \psi(2^{l} x - k). \tag{12}$$

Let $\mu^{\tau}_{j} = h^{\tau}_{3}(j/8)$, which is equal to the average of $h^{\tau}(x)$ in the range of $j/8 \le x < (j+1)/8$. We measure the similarity based on μ^{τ}_{j} and $\gamma^{\tau}_{l,k}$ not $h^{\tau}(x)$ itself. We define the vector $\xi^{\tau}_{j} = \left(\mu^{\tau}_{j}, \gamma^{\tau}_{3,j}, \gamma^{\tau}_{4,2j}, \gamma^{\tau}_{4,2j+1}, \gamma^{\tau}_{5,4j}, \gamma^{\tau}_{5,4j+1}, \gamma^{\tau}_{5,4j+2}, \gamma^{\tau}_{5,4j+3} \right)$ for $0 \le j \le 7$.

Although we used the RGB color model in Section 2.1, we use the L*a*b* color model. The value of L* represents the lightness of the color, a* represents the position between red and green and b* represents the position between yellow and blue. In fact, most labels have a white background, which is one reason why the labels resemble each other. The reason for using this model is that it is easy to separate the degree of freedom related to white, namely, lightness L*. In order to neglect this degree of freedom, we set $\mu^{\tau}_{j} = 0$ for L*.

Finally, we join the vectors by direct sum:

$$\rho_j^\tau = (\xi^L)_j^\tau \oplus (\xi^a)_j^\tau \oplus (\xi^b)_j^\tau,$$

and define the average similarity of the parts of labels as

$$sim^W_{j,j'} = \operatorname*{avg}_\tau \frac{\rho_j^\tau \cdot \rho'^\tau_{j'}}{\|\rho_j^\tau\| \, \|\rho'^\tau_{j'}\|},$$

and the similarity of the whole labels as

$$sim^W = \max_k \frac{1}{8} \sum_j sim^W_{j,j+k}.$$

3 Experiments

We estimated our methods by applying them to the ampoule labels provided in the market. The targets were the 12 labels shown in Fig. 2. Since each of the label images has a different size, we adjusted the size to 157-pixel height and 256-pixel width by means of linear interpolation method.

3.1 sim^f

Fig.2 shows the pairs of labels and their values of similarity index sim^f in descending order. The pair, Label6 and Label7, and the pair, Label8 and Label9, are respectively very similar designs that have the same colors. The pair, Label5 and Label6, and the pair, Label5 and Label8, have similar design but different colors, and their values of sim^f are less than those of the above pairs. These facts are compatible with our intuition.

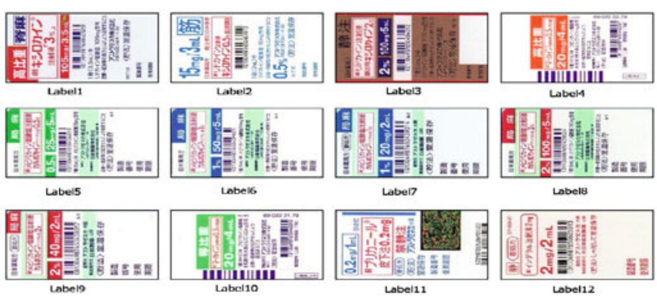

Fig. 2. The sample labels for the experiment

Table 1. sim^f for the pairs of the labels in Fig.2

Order	Labels		Color		Design w/o color		sim^f
	X	Y	sim^{color}	rank	$sim^{pattern}$	rank	
1	6	7	0.9990	1	0.7165	7	0.9546
2	8	9	0.9989	2	0.7303	6	0.9546
3	9	12	0.9979	3	0.6328	13	0.8939
4	5	6	0.9945	14	0.7678	4	0.8788
5	5	8	0.9936	18	0.8004	2	0.8636
6	9	11	0.9934	20	0.6345	12	0.8409
7	4	9	0.9970	6	0.5717	27	0.7576
8	8	11	0.9939	17	0.6208	17	0.75
9	5	7	0.9919	26	0.6984	8	0.7424
10	2	6	0.9977	4	0.5523	31	0.7424
⋮							
62	3	11	0.9457	61	0.5287	41	0.2424
63	10	12	0.9874	41	0.4372	64	0.2197
64	3	12	0.9679	56	0.5038	44	0.2121
65	1	10	0.9835	49	0.4422	63	0.1667
66	3	10	0.9363	63	0.4492	62	0.0682

So are the pairs that have small sim^f values. This is also compatible with our intuition, since their design and color is different.

The pair, Label9 and Label12, also has a large sim^f value, though they can be intuitively recognized to be different. In detail, we can see that their base colors are red and that the position and size of the bar code are similar. In fact, Label12 has a relatively large sim^{design} value with Label5, Label6, Label7, Label8 and Label9. The void (white) parts at their upper right are wider than the others and therefore have large RGB values in large areas. The pattern of the void parts makes their $sim^{pattern}$ value large. In spite of these facts, they seem to be different. This suggests that the contribution of the void parts is larger than the contribution of different parts between labels.

3.2 sim^w

The pairs that have high sim^w value are the combinations of Label5, Label6, Label7, Label8 and Label9. It is easy to see that the results reflect the difference of design such as the width of colored stripes with standard units (e.g. 1% 20 mg/2 ml) rather than their colors. We consider that this comes from the characteristics of the multi-resolution analysis (MRA) based on Haar's wavelets, since MRA measures the scale of the stripe width.

The exception is the pair, Label1 and Label2. It is notable that the letters in the right half of Label1 are printed only in black and the right half of Label2 has a similar layout of letters apart from their color (blue). We should remember that black and white have only L* values (namely a* and b* are zero) and that blue color has a nonzero L* value. Since we defined the similarity based on an inner product of the vectors ρ_j^r, and since $\xi_j^{ar}=0$ and $\xi_j^{br}=0$ for the right half of Label1, if the vectors ξ_j^{Lr} for the two labels are almost parallel, sim^W has a large value. This condition means that the labels have a similar design.

In this experiment, the average of $sim^W_{j,j+k}$ for the pair, Label5 and Label10, was maximized to be 0.1951 when the parameter k was 1. Although both of these have similar green parts, the positions where green parts exist in the labels have minor deviation. The result k=1 indicates that shifting Label10 to the left as much as 256/8=32 pixels makes the labels look most similar.

Table 2. sim^W for the pairs of the labels in Fig.2

Order	Labels		sim^W
	X	Y	
1	5	6	0.4250
2	6	8	0.4198
3	7	9	0.4070
4	5	8	0.3715
5	6	9	0.3192
6	8	9	0.2803
7	1	2	0.2471
8	5	9	0.2283
9	7	8	0.2235
10	6	7	0.2076
	⋮		
62	2	5	0.02837
63	1	10	0.01114
64	3	7	0.006361
65	2	8	0.004041
66	4	7	0.000142

3.3 Comparison of sim^f and sim^W with the Results of a Questionnaire Survey

We conducted a questionnaire survey to compare our similarity indices with the subjective estimation of similarities answered by respondents. We presented two pairs of labels to respondents and asked them to answer which pair was more similar than the other.

The respondents were 10 university students.

For both sim^f and sim^W, the pair that has a higher similarity value is more selected by respondents than the other in about 72% of cases (8 cases out of 11 cases). Especially for the cases that a pair has $sim^W \geq 0.10$ the other has $sim^W < 0.10$, more than 90% of respondents tended to answer that the former pair is similar. This suggests that our similarity indices tend to coincide with the similarity felt by humans.

As we explained, the void part in the background of labels tends to enlarge the value of sim^f . The result suggests that this holds for Case 2, Case 3 and Case 4.

As for sim^w , Label3 tends to have large values with other labels as is seen in Case 6 and Case 8. This is because sim^w ignores the brightness/darkness of the background and tends to focus on the design rather than colors. This can cause a high value of sim^w even though the background color is different.

These facts suggest that the key is how to deal with bulk (background) colors of labels and reflect them in similarity indices.

Table 3. Comparison of sim^f and sim^w with the results of the questionnaire

Case	Combination A				Combination B			
	labels	sim^f	sim^w	#res	labels	sim^f	sim^w	#res
1	*2,6*	**0.75**	**0.063**	**6**	*7,11*	0.58	0.041	4
2	*2,6*	**0.75**	0.063	1	*5,10*	0.55	**0.20**	**9**
3	*1,8*	0.58	0.035	**7**	*9,12*	**0.89**	**0.11**	3
4	*9,11*	**0.77**	0.039	2	*4,10*	0.59	**0.16**	**8**
5	*4,7*	0.40	0.00014	4	*5,11*	**0.64**	**0.039**	**6**
6	*3,8*	0.45	**0.081**	1	*1,12*	**0.51**	0.056	**9**
7	*2,7*	0.62	0.068	2	*7,8*	**0.64**	**0.22**	**8**
8	*4,9*	**0.77**	0.082	**9**	*3,6*	0.36	**0.11**	1
9	*4,12*	0.56	0.096	1	*6,8*	**0.72**	**0.42**	**9**
10	*9,12*	**0.89**	**0.11**	**10**	*4,5*	0.41	0.072	0
11	*2,10*	0.41	0.034	1	*5,6*	**0.88**	**0.43**	**9**

4 Conclusion

In order to design a similarity index for ampoule labels, we discussed how to extract data that contain the information of their characteristics. In this paper, we introduced methods based on Fourier series expansion and wavelet transformation.

As for Fourier series expansion, we separately dealt with the constant component and other components. This is because the constant term is a set of the mean values of each color and the other terms contain information of the extent of variation from the mean values of each color. We defined a similarity index for each of these components and combined them by means of their ranks in order to absorb the difference of their distribution.

We also introduced analysis that utilizes wavelet transformation based on Haar's wavelet in order to estimate similarity of not only the whole part of each label but also its part that is within the range of view. We defined a similarity index based on the cosine given by the inner product of the vectors whose elements are wavelet coefficients.

We also discussed the color parameterization. For Fourier analysis, we used the RGB color system, which is the most commonly used. In this paper, for the wavelet analysis, we also adopted L*a*b* in order to decompose the lightness elements from the color space.

We evaluated our methods by applying them to the ampoule labels provided in the market and compared the obtained similarity index values with the subjective estimation of similarities responded by examinees.

For both similarity indices, the pair that has a higher similarity value is more selected by respondents than the other in about 72% of cases (8 cases out of 11 cases).

The void part in the background of labels tends to enlarge the value of the similarity index based on Fourier series decomposition. The similarity index based on our wavelet analysis ignores the brightness/darkness of the background and tends to focus on the design rather than colors. These facts suggest that the key is how to deal with bulk (background) colors of labels to reflect them in similarity indices.

In the next step, we will propose a method of dealing with the background color of labels. It is not straightforward, since white background color is too common to be the characteristic of labels though the other background color is sensitively recognized to be a characteristic.

Although we ignored the color, size and material of the container part of ampoules, they can have a large impact on similarity. In the future, we will combine their contributions with our method.

References

1. Tsuchiya, F., Kawamura, N., Oh, C., Hara, A.: Standardization and similarity deliberation of drug-names. Japan Journal of Medical Informatics 21(1), 59–67 (2001)
2. Nabeta, K., Imai, T., Kimura, M., Ohkura, M., Tsuchiya, F.: The similarity index of medicine names to prevent confusion. In: Proceedings of Pan-Pacific Conference on Ergonomics 2010, Taiwan (2010)
3. Daubechies, I.: Ten Lectures on Wavelets. Society for Industrial and Applied Mathematics, Philadelphia (1992)