Generic Promotion of Diffusion-Based Salient Object Detection

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Supplemental Material

In this supplemental material, we further analyze our algorithm and show more visualization results.
Firstly, we give the derivation of Eq. 5 in our submitted paper and thus clarify the working mechanism of our seed vector.
Secondly, we extend Fig. 1 in our submitted paper by giving more visualization of normalized eigenvectors.

1. Seed Vector Mechanism

1.1. Absorbed Time

Eq. 5 in our paper is not the original expression in the work [1], in this section we will derive it and thus clarify the working mechanism of our seed vector.

Work [1] computes the absorbed time for each node as its saliency value, duplicates the superpixels around the image borders as the virtual background absorbing nodes, and sets the inner nodes as transient nodes, thus constructing an Absorbing Markov Chain. In its original formula,

$$P = D^{-1}W = \begin{pmatrix} Q & R \\ 0 & I \end{pmatrix}, \tag{1}$$

where the first m nodes are transient nodes and the last $N-m$ nodes are absorbing nodes, $Q \in [0,1]^{m\times m}$ contains the transition probabilities between any pair of transient nodes, while $R \in [0,1]^{m\times(N-m)}$ contains the probabilities of moving from any transient node to any absorbing node. 0 is the $(N-m)\times m$ zero matrix and I is the $(N-m)\times(N-m)$ identity matrix. Thus, the absorbed time for m transient nodes is:

$$y^* = (I-Q)^{-1}c = (Q^0 + Q^1 + Q^2 ...)c, \tag{2}$$

where c is an m dimensional column vector whose elements are all 1.

Obviously, the absorbed time for absorbing nodes is 0, thus we define the absorbed time for all the N nodes as $y = \begin{pmatrix} y^* \\ 0 \end{pmatrix}$. And since

$$P^n = \begin{pmatrix} Q^n & (Q^0 + Q^1 + ... + Q^{n-1})R \\ 0 & I \end{pmatrix} \tag{3}$$

we have

$$\begin{aligned} y &= (P^0 + P^1 + P^2 ...)x = (1-P)^{-1}x \\ &= (D^{-1}(D-W))^{-1}s = L_{rw}^{-1}x, \end{aligned} \tag{4}$$

where $x = \begin{pmatrix} c \\ 0 \end{pmatrix}$. Further, as proved by our submitted paper,

$$\begin{aligned} y_i &= \sum_{j=1}^{N} x_j \left\langle \Psi_{L_{rw\,i}}, \Psi_{L_{rw\,j}} \right\rangle, \\ &= \sum_{j=1}^{m} \left\langle \Psi_{L_{rw\,i}}, \Psi_{L_{rw\,j}} \right\rangle \end{aligned} \tag{5}$$

meaning that the absorbed time of each node is equal to the sum of the inner products of its diffusion map with those of all the m non-border nodes on the Absorbing Markov Chain.

1.2. Seed Vector

Our seed vector is defined as:

$$\tilde{s} = \widetilde{A}^{-1}x,$$
$$\tilde{s}_i = \sum_{j=1}^{m} \left\langle \Psi_{\tilde{A}_i}, \Psi_{\tilde{A}_j} \right\rangle \quad (6)$$

where $x = (x_1, \ldots, x_N)$ with $x_i = 1$ if v_i is a non-border node and $x_i = 0$ otherwise.

In effect, after connecting all the nodes at the four borders of the image, we have constructed a graph similar to the Absorbing Markov Chain. For every node at the border, it connects with all bn border nodes (including itself) and only bm non-border nodes (usually, $bm \ll bn$), meaning that once a random walk reaches a border node, it will less likely escape from the border nodes set. Therefore, we may roughly assume that all the non-border nodes are transient nodes and all the border nodes are absorbing nodes.

Since, $\Psi_{\tilde{A}}$ and $\Psi_{L_{rw}}$ are only different at number of entries and the weight of each entry, the behavior of Eq. 6 is similar as Eq. 4 which computes the absorbed time of each node to random walk to the border nodes.

2. Visualization of Normalized Eigenvectors

In this section, we show more visualization of normalized eigenvectors in Figures 1-16. The first column are source images, the second column are ground truths, the third column are our saliency maps, and from the fourth to the last columns are the normalized eigenvectors (from u_2 to u_{15}). We use white borders to indicate that the variance of this eigenvector is below our threshold v and use a red margin between two successive eigenvectors to indicate an eigengap (All the eigenvectors, u_2 to u_{15}, are before eigengap, if there is no red margin in that row.). We can see that the eigenvectors before the eigengap usually well indicate node clusters, though sometimes some tiny salient regions may be captured by some eigenvectors.

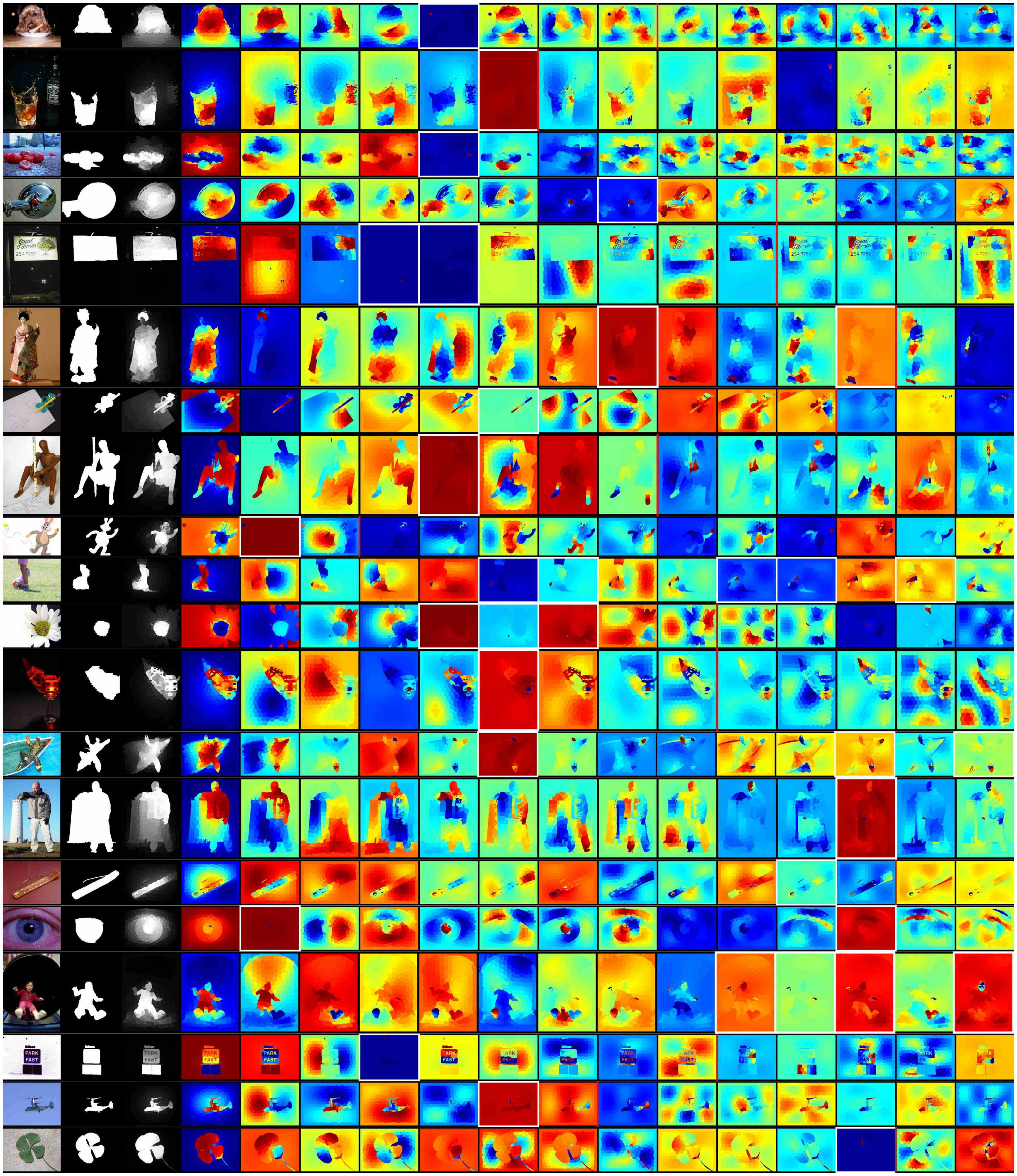

Figure 1. Visualization of normalized eigenvectors.

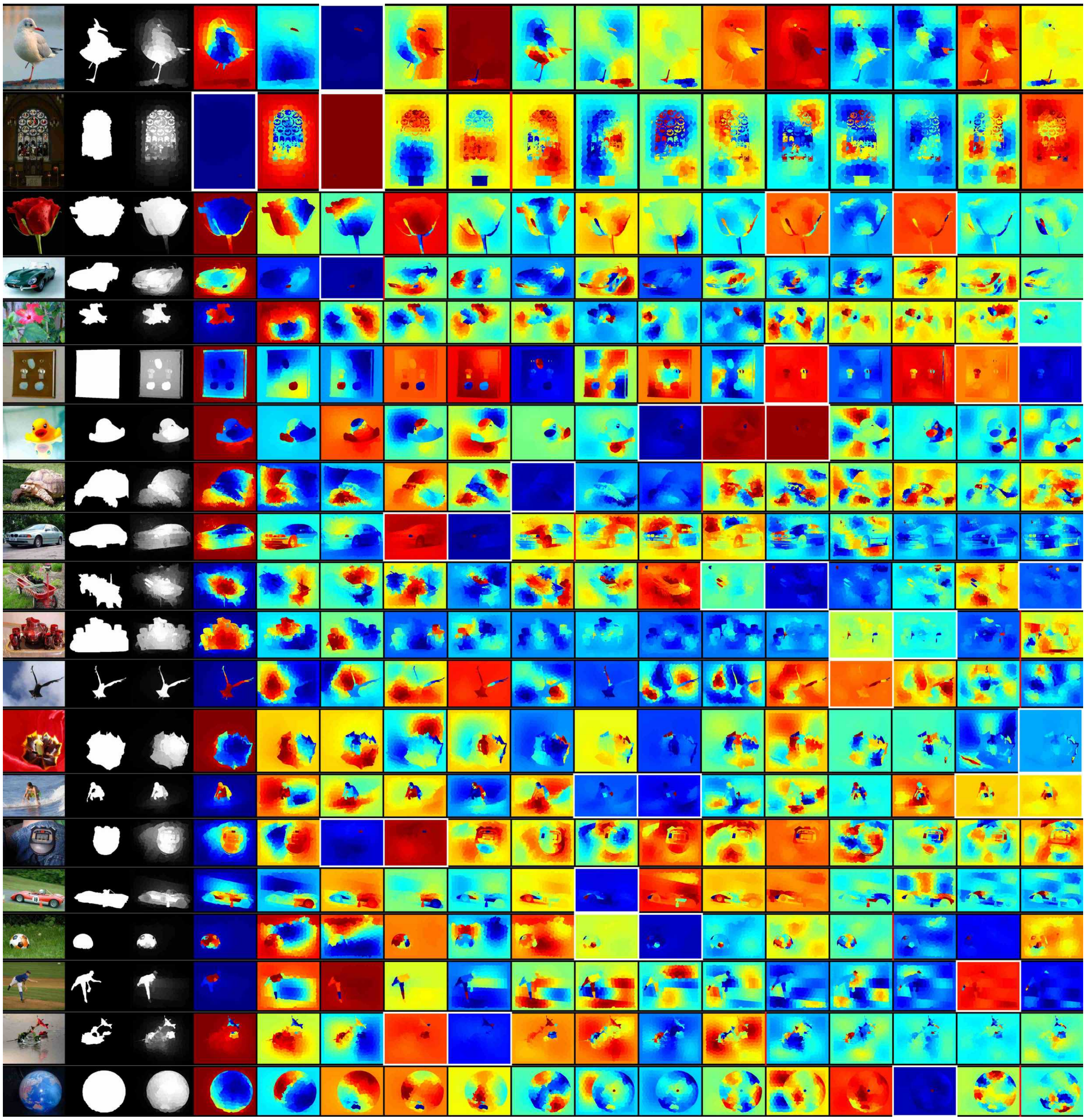

Figure 2. Visualization of normalized eigenvectors.

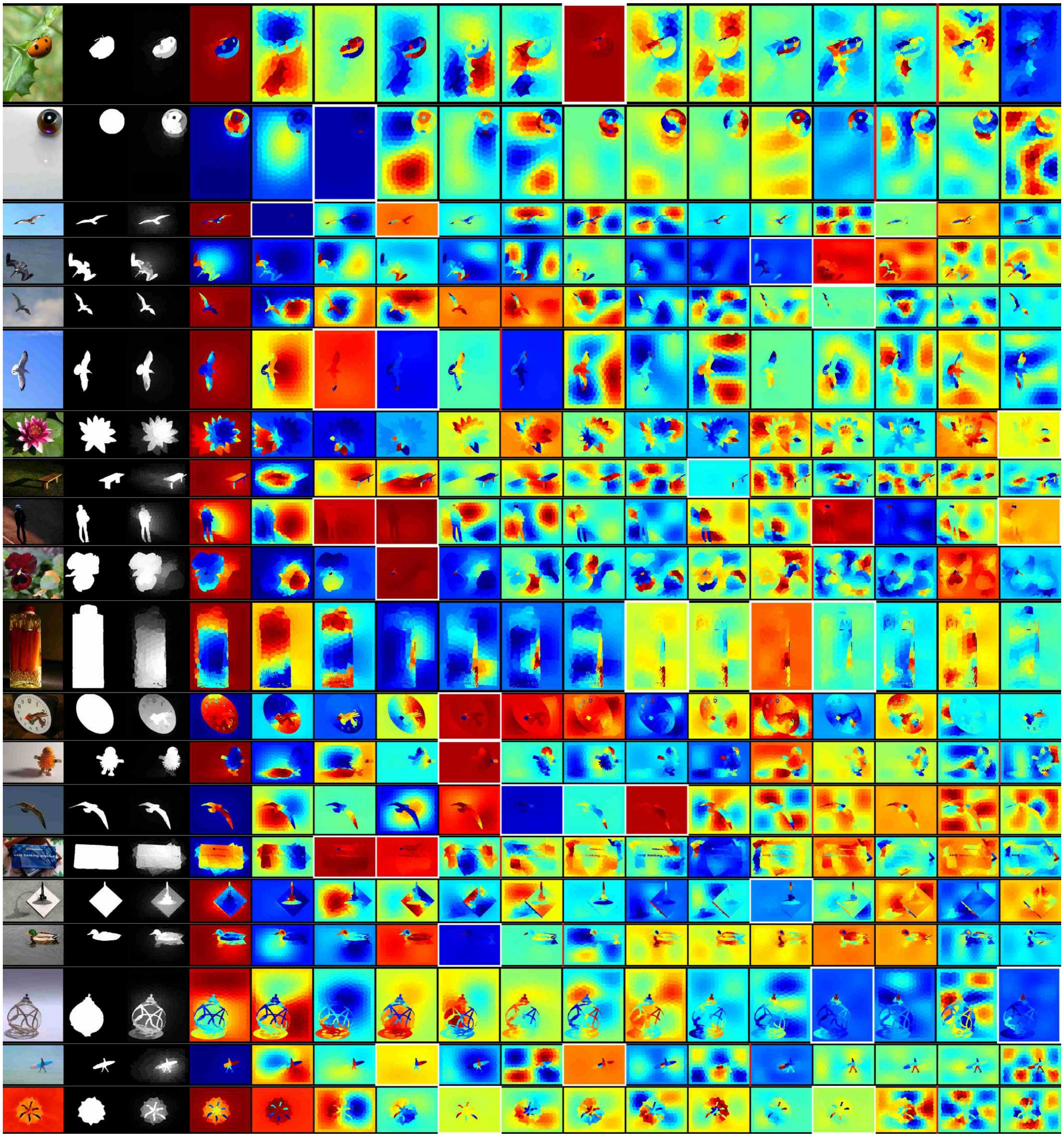

Figure 3. Visualization of normalized eigenvectors.

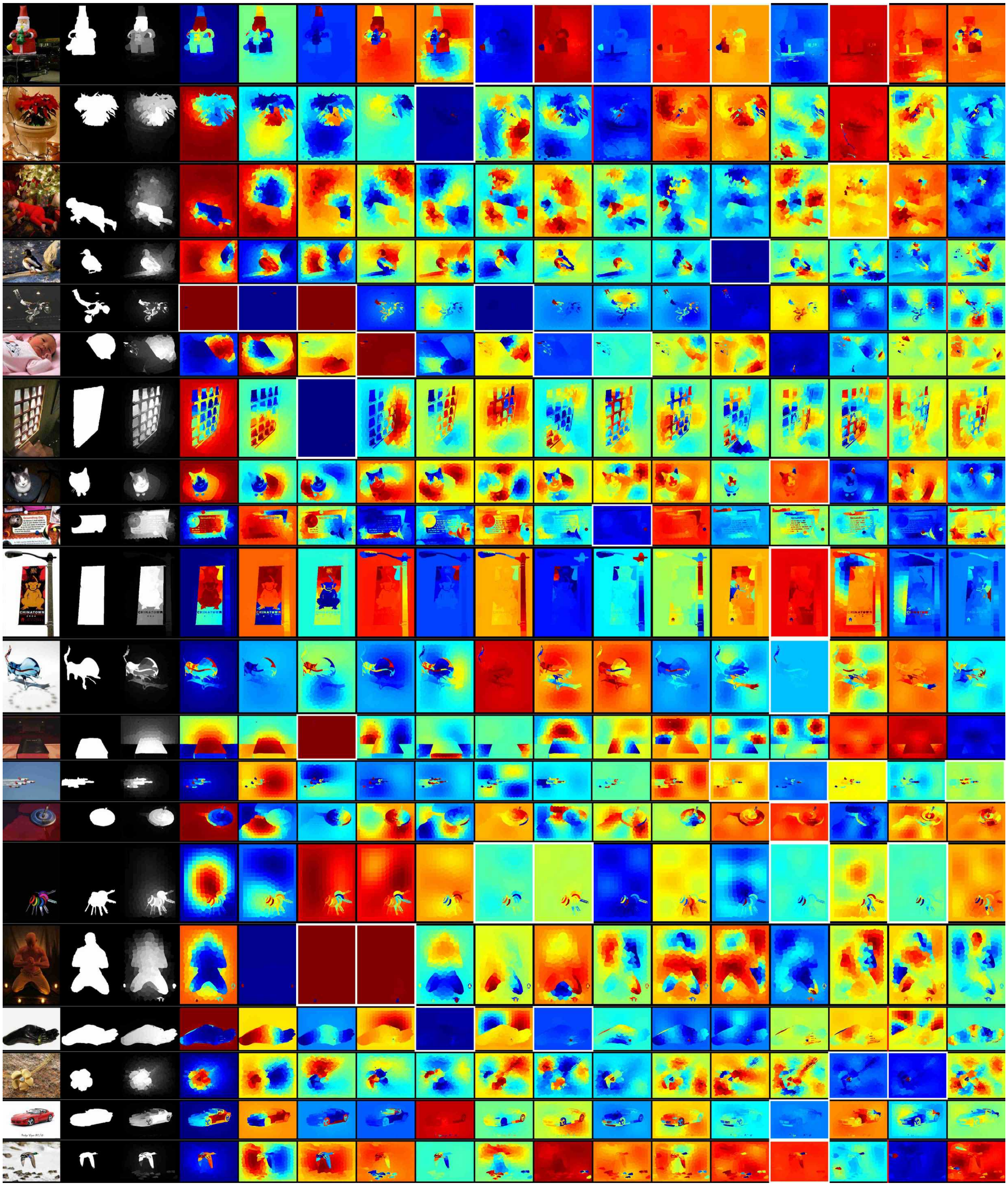

Figure 4. Visualization of normalized eigenvectors.

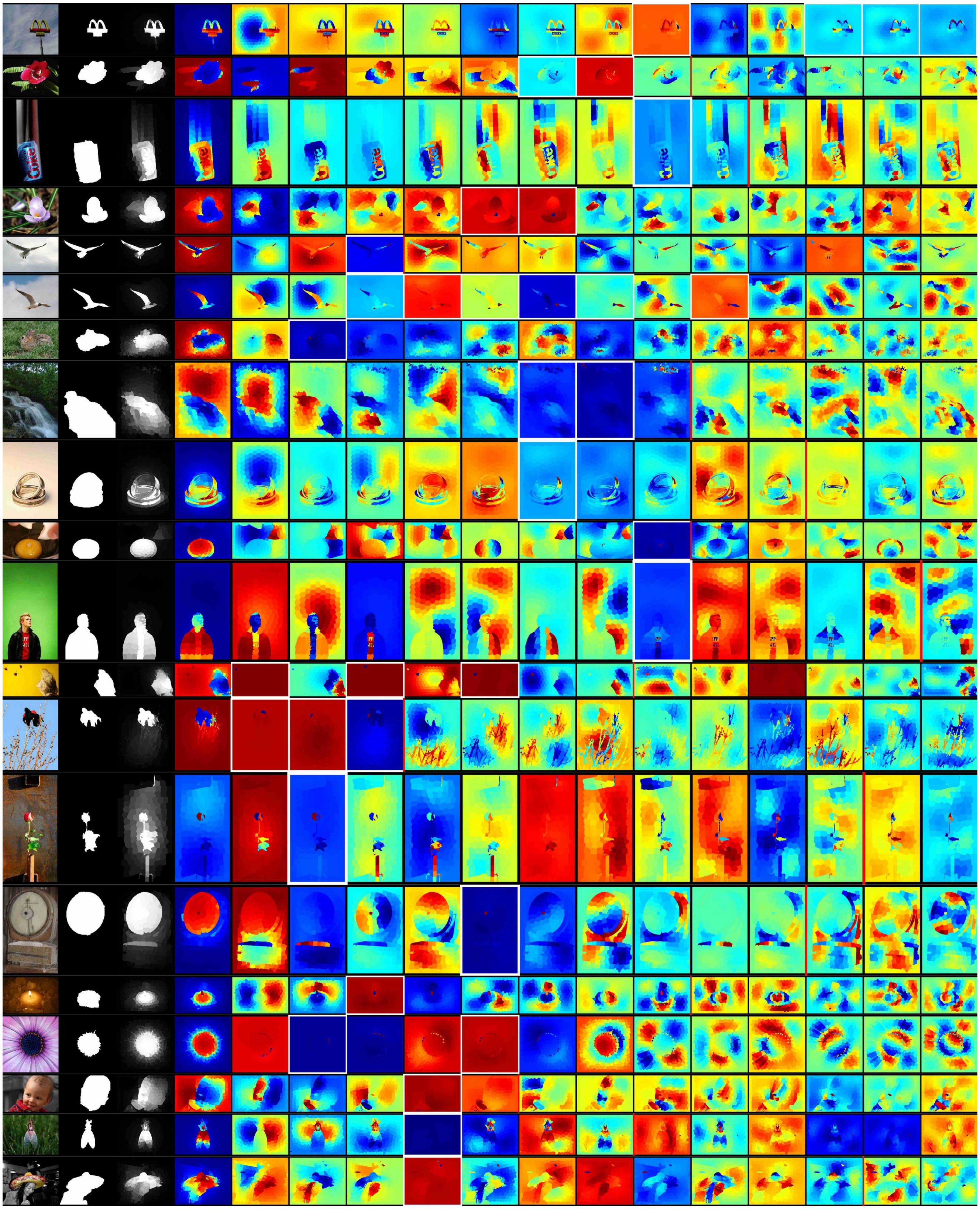

Figure 5. Visualization of normalized eigenvectors.

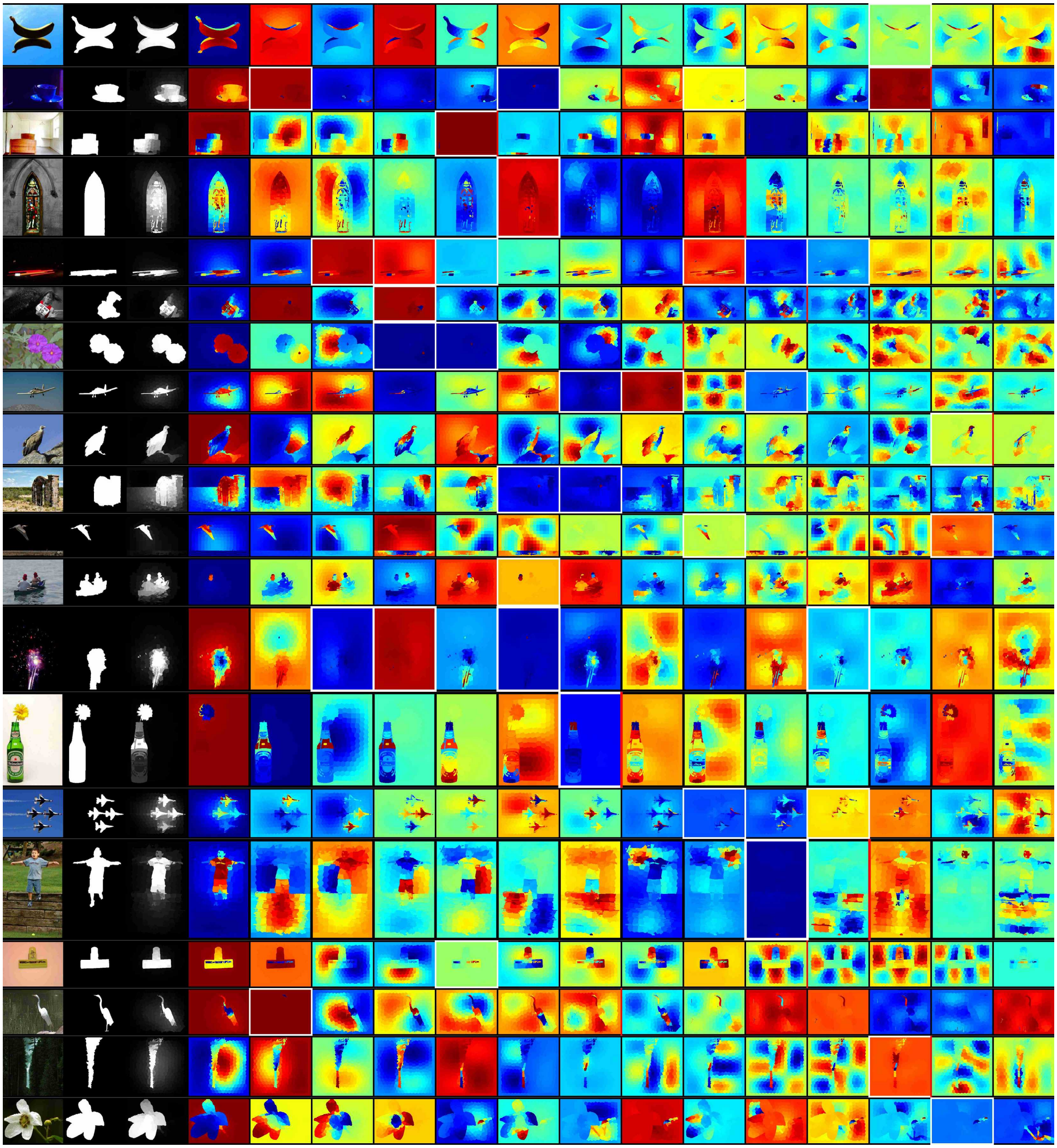

Figure 6. Visualization of normalized eigenvectors.

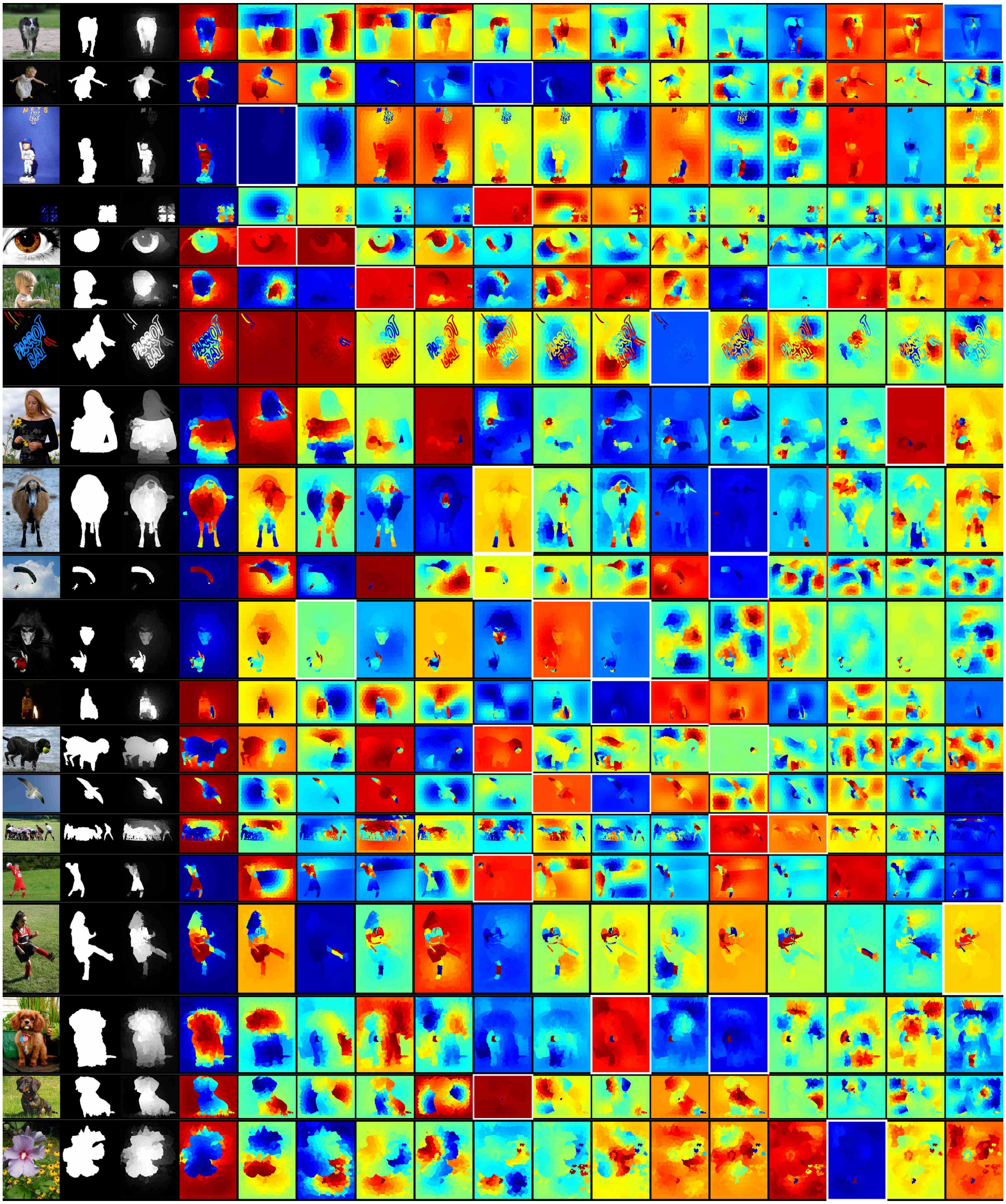

Figure 7. Visualization of normalized eigenvectors.

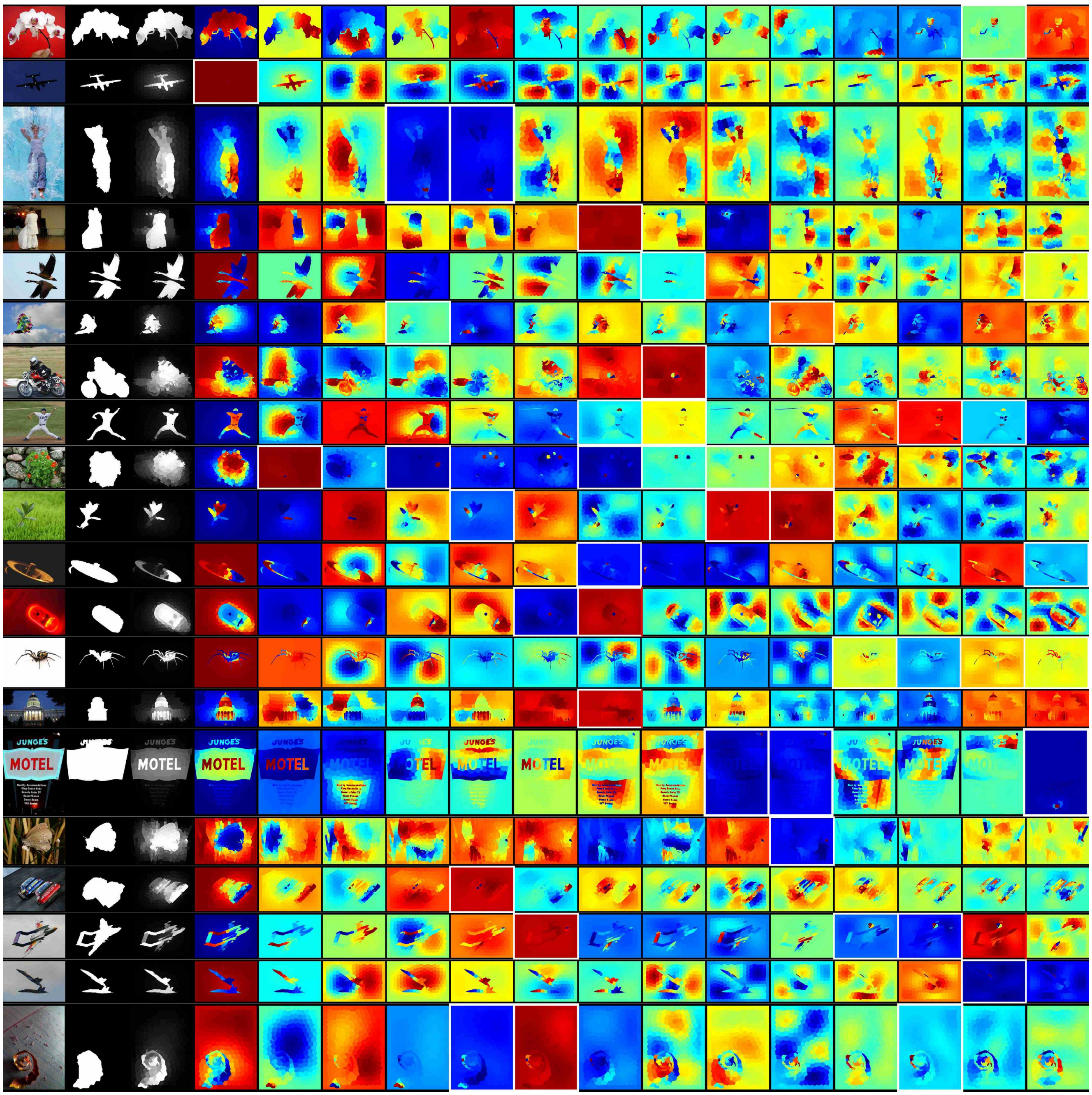

Figure 8. Visualization of normalized eigenvectors.

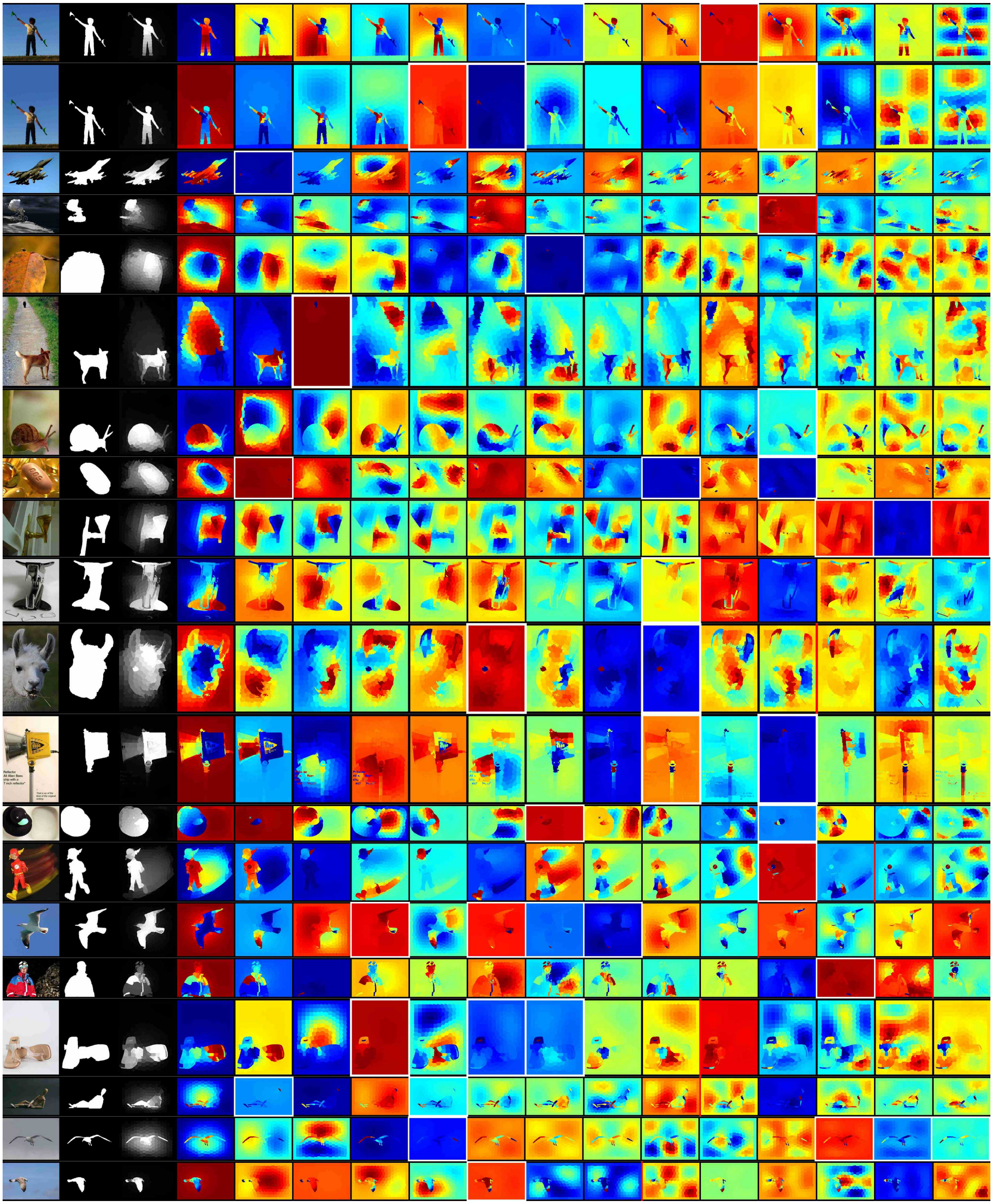

Figure 9. Visualization of normalized eigenvectors.

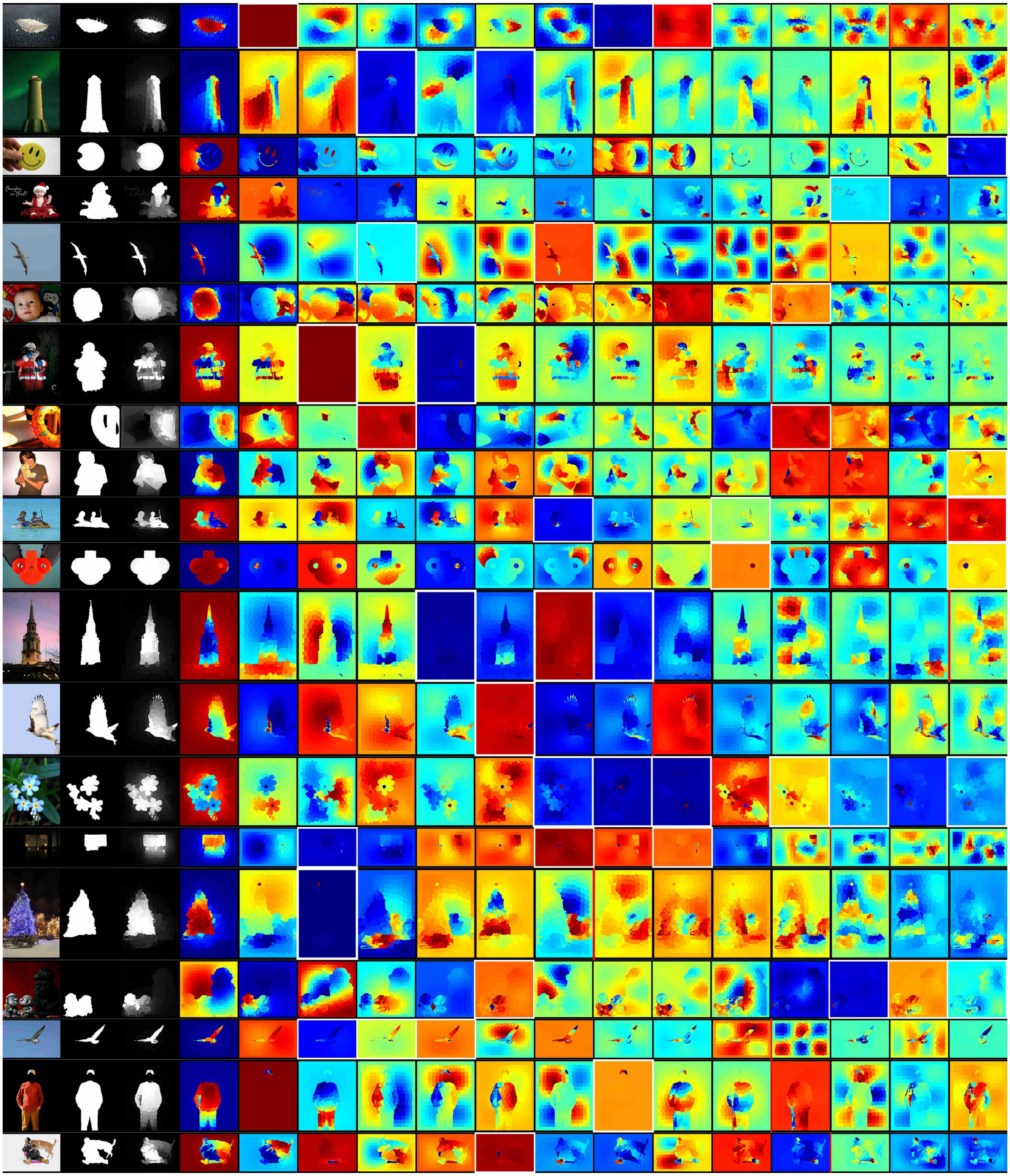

Figure 10. Visualization of normalized eigenvectors.

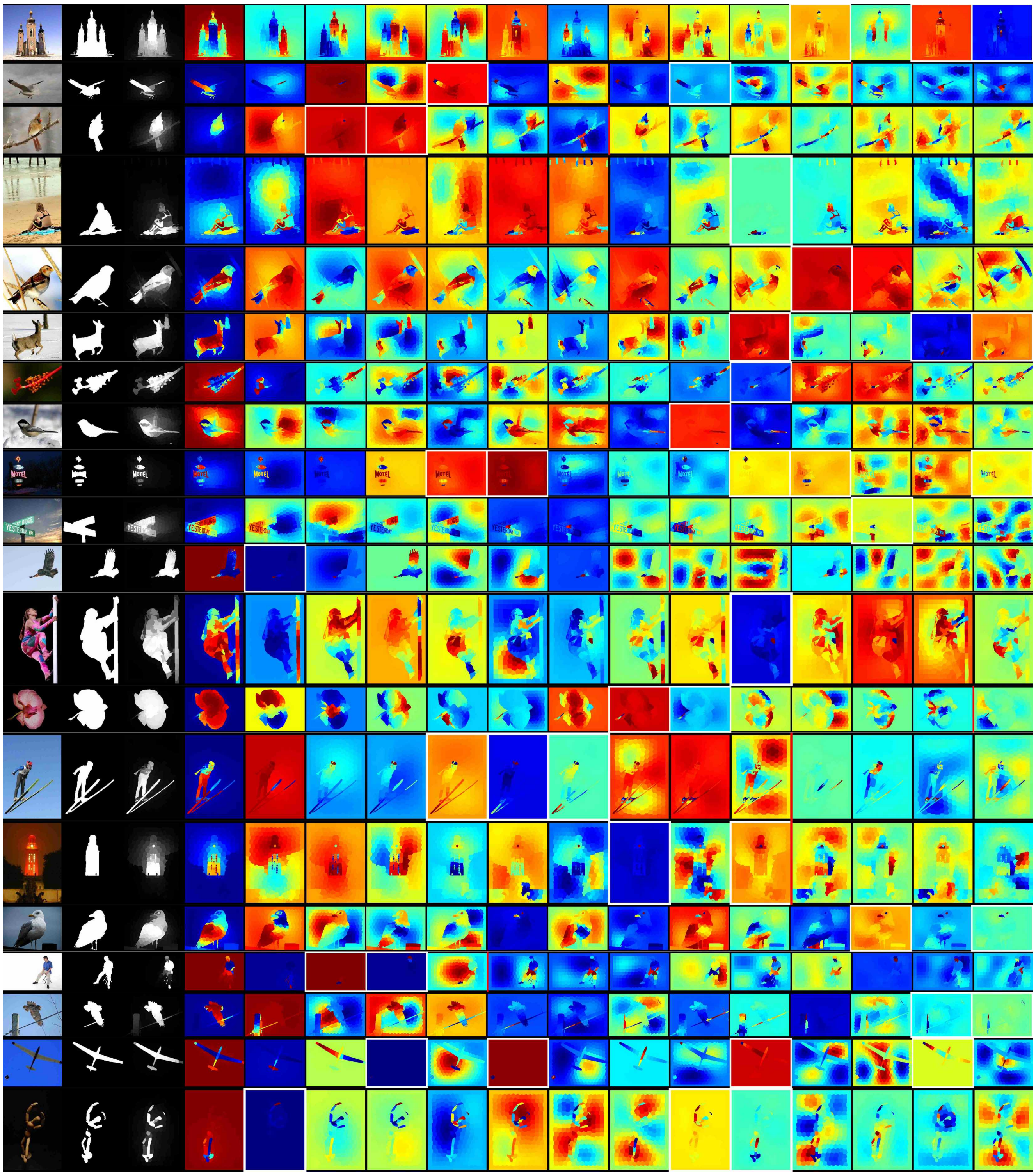

Figure 11. Visualization of normalized eigenvectors.

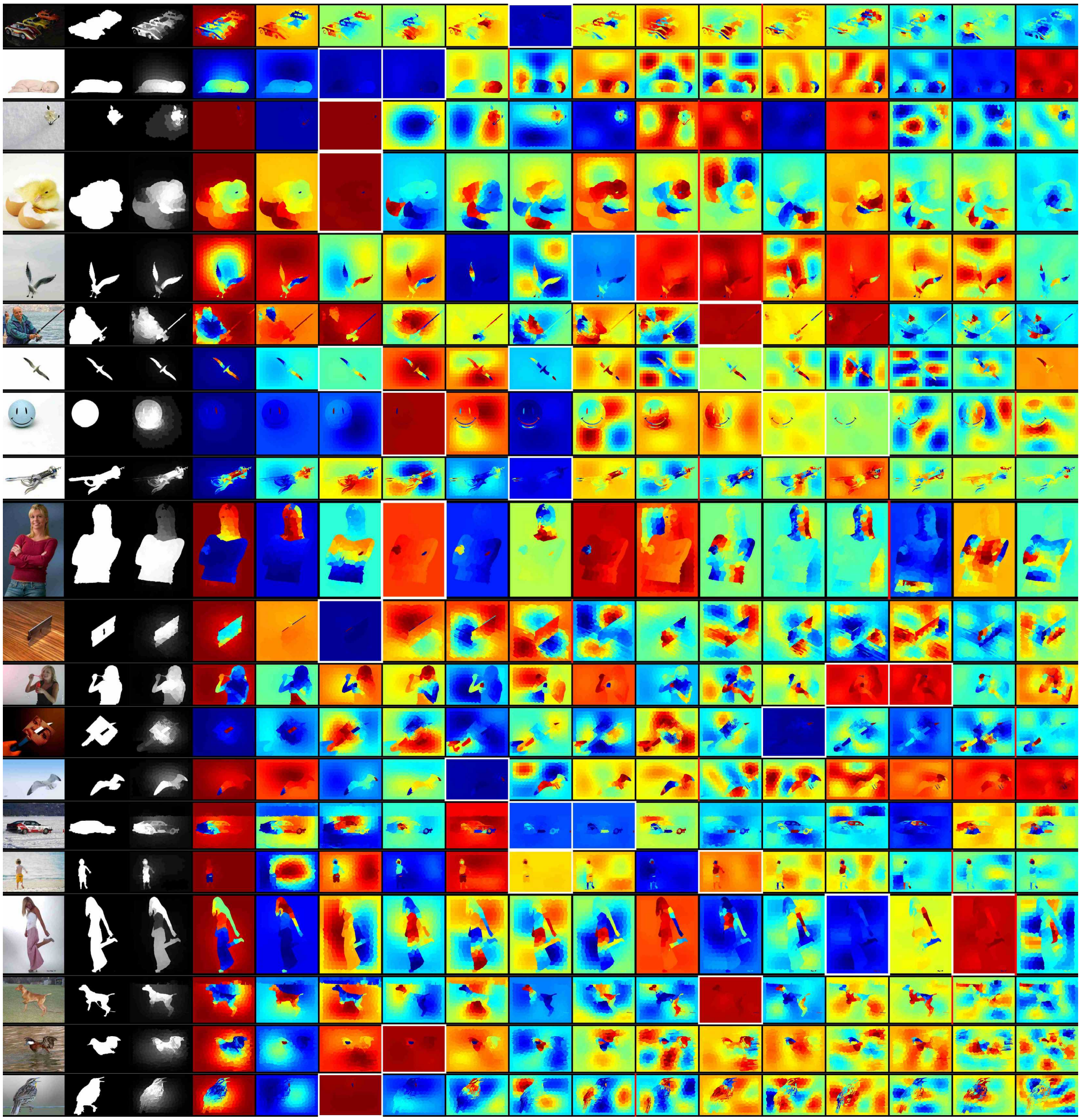

Figure 12. Visualization of normalized eigenvectors.

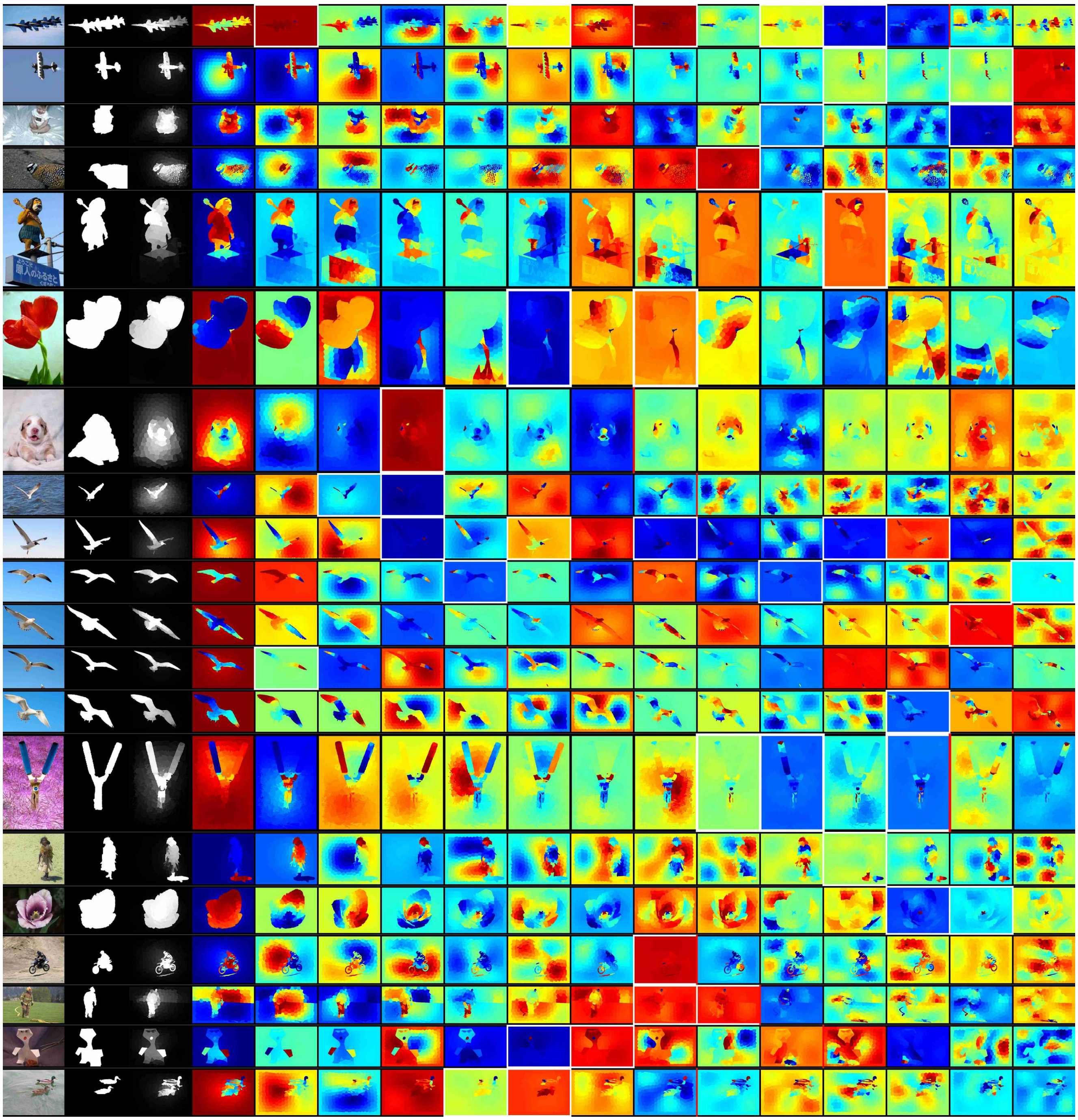

Figure 13. Visualization of normalized eigenvectors.

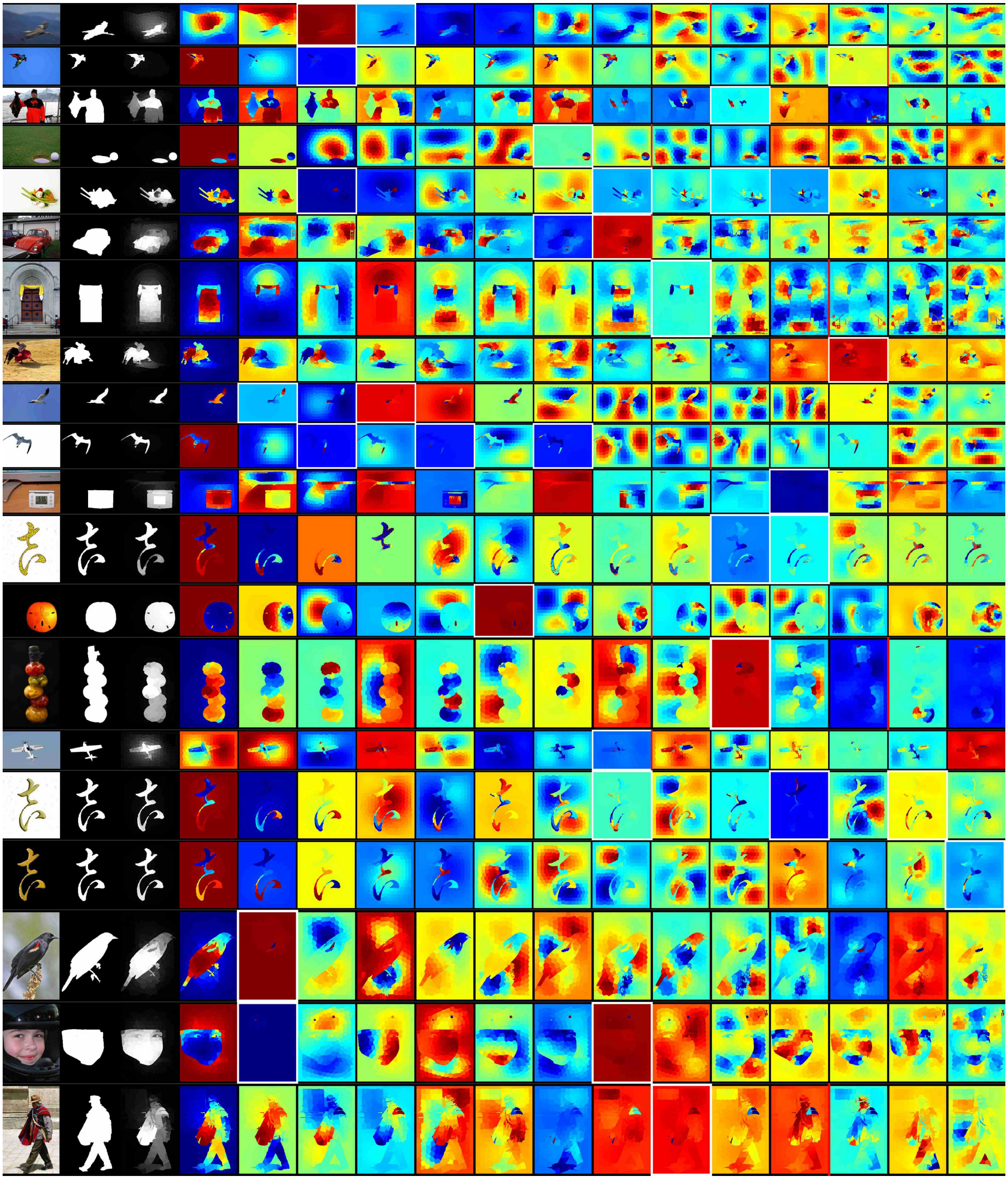

Figure 14. Visualization of normalized eigenvectors.

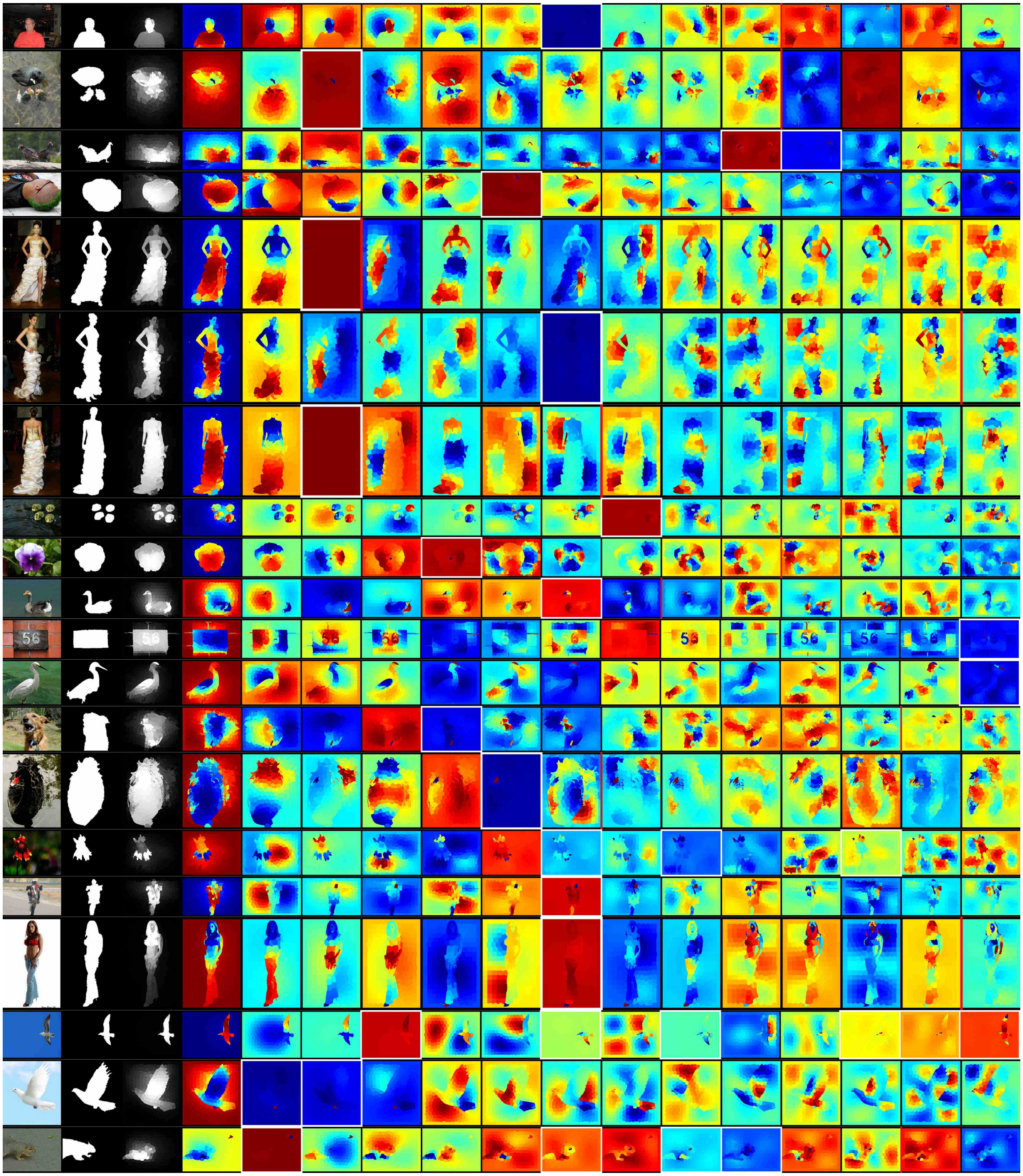

Figure 15. Visualization of normalized eigenvectors.

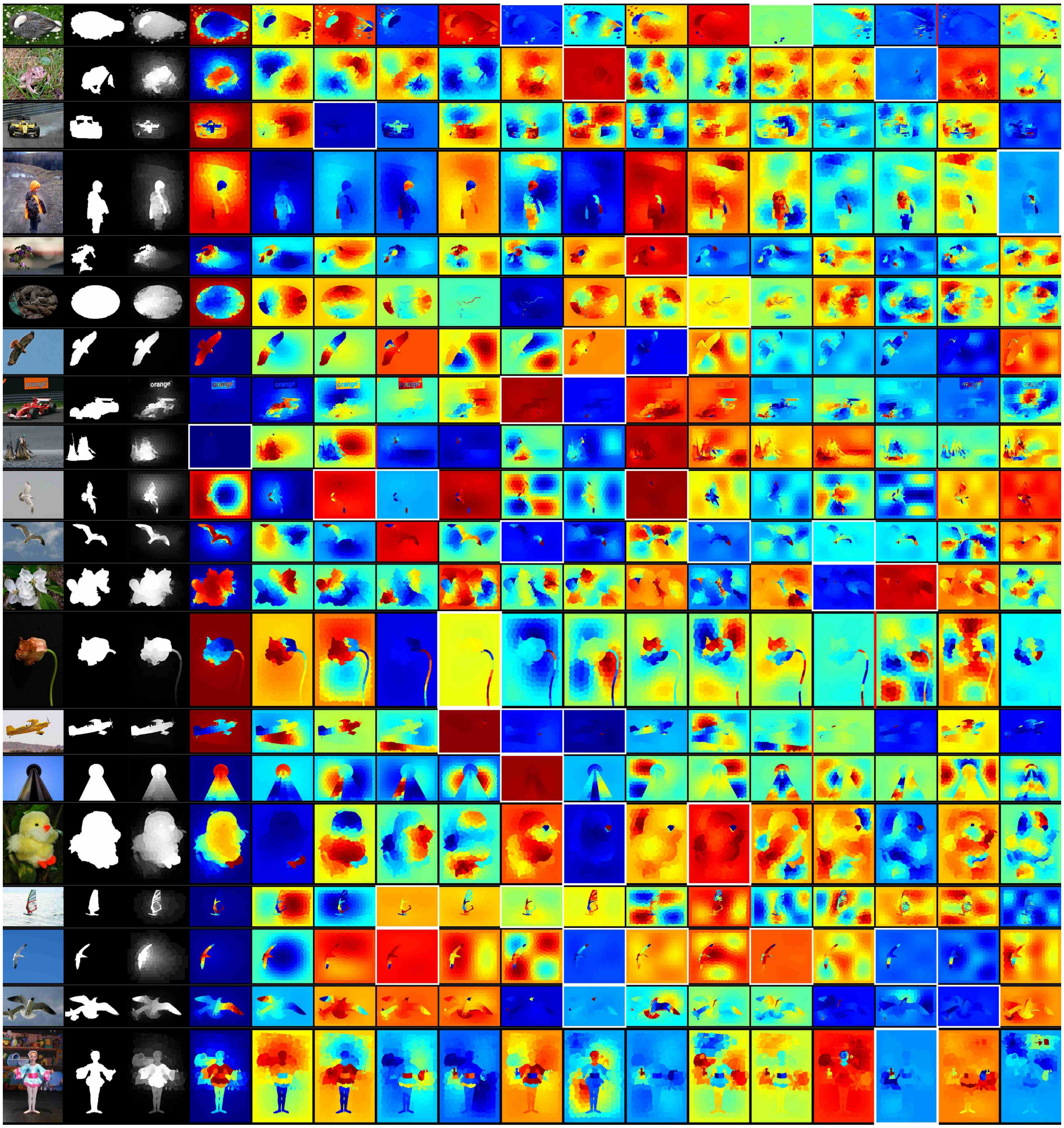

Figure 16. Visualization of normalized eigenvectors.

References

[1] B. Jiang, L. Zhang, H. Lu, C. Yang, and M.-H. Yang. Saliency detection via absorbing markov chain. *ICCV*, 2013. 1