F. Holland Day art photographic paper clustering: Automated procedures to assist photograph conservators ?

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Résumé – Une collection de 149 photographies de F. Holland Day a été constituée par des conservateurs de photographies, spécialistes de cet artiste. Des échantillons d'environ un centimètre carré de textures des papiers photographiques correspondants ont été numérisés et mis dispositions d'équipes de traitement d'images, avec pour objectif l'évaluation de l'intérêt et de la pertinence d'une classification non supervisée automatisée. Une procédure, combinant représentations anisotropes multiéchelles et clustering spectral, déjà mise en oeuvre dans plusieurs challenges de classification automatique de papiers photographiques, a été complétée ici par la conception d'un indice quantifiant la robustesse de la classification. La comparaison de la classification obtenue celle réalisée a priori et indépendamment par les conservateurs par inspection visuel des papiers a permis d'intéressantes réflexions interdisciplinaires.

Abstract – Photograph conservators assembled a collection of 149 photographs by F. Holland Day. Digitized one-squared centimeter samples of textures of the corresponding papers were made available to image processing teams, with the aim of assessing the potential interest and efficiency of automated unsupervised clustering. A procedure combining anisotropic multiscale representations and spectral clustering, already used in art photographic paper clustering challenges, was complemented with the design of a clustering robustness index. Comparisons of the achieved automated clustering against an a priori and independent grouping performed by visual inspection of the textures by photograph conservators triggered fruitful interdisciplinary interactions and discussions.

1 Introduction

F. Holland Day (1864-1933) was a leader in the art photography movement known as Pictorialism (1885-1915), which had its founding at the turn of the nineteenth century [5, 4]. This movement was the first to promote photography as an artistic medium on par with other graphic and visual arts. While Day was an important figure in photography, his career spanned roughly 20 years, and due to a studio fire in 1904, much of his work does not survive. The Library of Congress is in possession of the largest collection of Day photographic prints in the world, totaling some seven hundred items, spanning the history of his career. These prints having unquestionable provenance are ideal for study and the focus of on-going research to define Day's working methods.

One fundamental aspect of photography is the paper, which imparts expressive texture to the final image. Understanding and being able to differentiate the textures of papers used throughout Day's career would provide key information on the choices he made in the darkroom, and further contribute to the dating and attribution of his work. Art photographic classification is commonly achieved by photograph conservators through visual inspection, which proved difficult and extremely time consuming over such a large collection, as visual memory for texture is limited and easily confused. Automation is thus seen as essential to the viability of texture comparison as a reliable method, as it is expected to be more objective, less time consuming, and to enable to compare objects across institutions. Relations between automated clustering and photograph conservator grouping constitute the core of the present work.

Related works. In 2007, a project conducted at the Museum of Modern Art made a pionnering attempt in automated classification of art photographs. Several image processing teams were invited to perform unsupervised clustering based on art art photographic paper texture similarity assessment on a subset of around 2000 digitized samples from the Yale Lens Media Lab (LML) Reference Collection of Photographic Papers [8]. These methods have demonstrated great promise on controlled data sets [2, 7, 9, 12, 1, 3].

Goal, contributions and outline. The present work elaborates of these first successes by comparing the automated clustering obtained from one of the image processing tools [2] against a grouping performed by the photograph conservators as well as in reporting both the photograph conservator comments and reactions to the automated clustering and issues in these interdisciplinary interactions. The dataset assembled by the photograph conservators involved in the present work together with the grouping procedure are described in Section 2. The anisotropic multiscale representation and spectral clustering used for automated classification are recalled in Section 3. An original noise-assisted procedure assessing the robustness of the clustering is devised and studied in Section 4. Finally, automated clustering and photograph conservator grouping are compared and discussed in Section 5.

2 DataSet

Dataset. A collection of $N = 149$ photos by F. Holland Day, was assembled by photograph conservators (experts in Days work and platinum paper), with the aim of differentiating the textures of papers used throughout Day's career [5, 4].
Data. For each photography, 1.00×1.35 cm^2 paper surface samples were digitized both recto and verso. Samples are digitized at 153.6 pixel/mm, thus producing 1536×2080 images (each pixel corresponding to $6.51^2 \simeq 42.4\,\mu$m^2), using a raking light imaging system, referred to as the *TextureScope*, and extensively described in [7].
Visual-inspection based Grouping. In the present work, groups of papers were assembled based on similarities in texture as established through visual inspection. Sorting was best done by establishing a *key set*, consisting of one image of each texture type, from which all others would be compared. This procedure resulted in a classification in nine groups, very different in size, labelled with letters A, B E, F, H, M, Q, S, and hereafter referred to as photograph conservator (PC) groups.

3 Multiscale Analysis/Spectral Clustering

The image processing tools used for automated art photographic paper characterization clustering have already been detailed in [2], and are hence here only briefly recalled.
Multiscale Analysis. Anisotropic multiscale analysis, proposed for the characterization of scale-free textures in [10], is implemented using the Hyperbolic Wavelet Transform (HWT). Expanding of the classical 2D-Discrete Wavelet Transform, HWT compares, by means of inner products, the texture to analyze X against wavelet templates, dilated with horizontal and vertical factors a_1, a_2 and translated at location k_1, k_2. Space averages $S_X(a_1, a_2)$ of squared HWT coefficients at scales a_1, a_2 define anisotropic multiscale features summarizing the key properties of texture X. To ensure both independence on image intensity and contributions from all scales, the $S_X(a_1, a_2)$ are log-normalized as $\tilde{S}_X(a_1, a_2) = \ln \frac{S_X(a_1,a_2)}{\sum_{a_1',a_2'} S_X(a_1',a_2')}$. Given the high-resolution images, a vector of 7 dyadic scales $a_1, a_2 = 2^j$ is used, ranging from 2 pixels (6.51μm) to 2^7 (834μm), for a total of $7 \times 7 = 49$ features $\tilde{S}_X(a_1, a_2, q)$. Distance between two images i and j is computed using a L^1 norm (or cepstral-like) distance :

$$\mathcal{D}(i, j) = \left(\sum_{a_1,a_2} |\tilde{S}_i(a_1, a_2) - \tilde{S}_j(a_1, a_2)| \right).$$

Clustering is achieved via Spectral Clustering (cf. e.g., [11, 6]), an unsupervised procedure aiming to reduce the dimensionality of texture representation space. A non-linear transformation is applied to the $N \times N$ distance matrix $\mathcal{D}$ to produce an Affinity matrix $\mathcal{A} = \exp(-\mathcal{D}/\epsilon)$, with ϵ a constant assessing a typical closeness between images. The (*random walk*) Laplacian operator of the graph underlying the structure of the Affinity matrix A, is diagonalized. The corresponding eigenvalues are sorted and the eigenvectors, $\{F_{i,k}\}$, corresponding to the $K \ll N$ smallest eigenvalues are assembled in a $K \times N$ matrix $\mathcal{S}$, defining the set of robust K coordinates. Ascendant clustering (Ward linkage), applied to matrix $\mathcal{S}$, yields a classification $C = \{C_k, k = 1 \cdots K\}$ into K clusters (with C_k the list of images in Cluster k).

4 Noise assisted robustness index

To assess the robustness of the achieved clustering C into K clusters, the following noise-assisted procedure is devised. For each image i, $Z = 10$ surrogate-copies $\{\tilde{F}_{i,k}\}$ of the spectral clustering features $\{F_{i,k}\}$ are generated by adding independently to each $\{F_{i,k}\}$ a white Gaussian noise, with standard deviation $\mu\sigma_k$, with σ_k the standard deviation of $\{F_{\cdot,k}\}$ and μ a tunable parameter. Ascendant clustering is then applied to the $K \times (N \times Z)$ matrix $\tilde{\mathcal{S}}$, as if the database consisted of $N \times Z$ original images, while keeping fix the number K of clusters, yielding classification $\tilde{C} = \{\tilde{C}_k, k = 1 \cdots K\}$. Then, for each image i in the original database, an index is computed as intersection size of clusters to which image i belongs for original and noise-blurred clusterings :

$$r_i = \frac{\#\{\tilde{c}_{k_i} \cap c_{k_i}\}}{\#\{c_{k_i}\}} \in [0,\ 1]$$

This is repeated for several noise levels and the final score robustness score $\overline{r}_i$ is computed as average of the r_i across noise levels, tuned by selecting μ. The underlying intuition of the proposed procedure is that when an image is very robustly classified within a cluster, it remains robust to additive noise. Conversely, when noise easily induces switches from one cluster to another, it indicates that the corrsponding image is not robustly clustered.

The procedure is assessed using synthetic data. Spectral clustering and the noise-assisted robustness procedure are applied to Features $\{F_{i,k}\}_{i=1,\ldots,80,k=1,\ldots,49}$, randomly generated according to a 4-class Gaussian mixture model, spanning the data into 4 equal size clusters. Spectral clustering easily identified

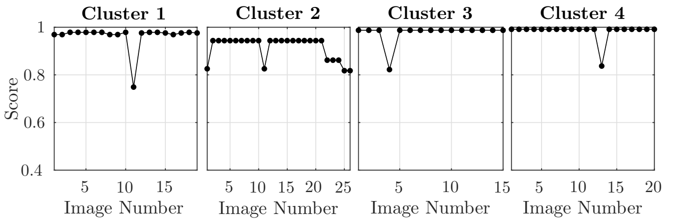

FIGURE 1 – **Robustness indices for each image per cluster.** Synthetic data.

the relevant number of clusters, $K = 4$. Fig. 1 reports robustness indices for each image per cluster. For Cluster2, images 1 and 21 to 26 are misclassified and interestingly have low robustness indices. In each of the 4 clusters, one image is observed to have a low robustness index despite actually belonging to the cluster. Detailed examination of the realization shows that these image are just *by chance* (features are randomly drawn) far from the center of the cluster they belong to (hence a low robustness index). These observations validates the relevance of the proposed clustering robustness index.

5 Automated clustering vs. photograph conservator grouping

5.1 Automated clustering and robustness indices

Matrix D_r (resp. D_v), of size $N \times N$, is computed as distances between the $N = 149$ recto (resp., verso) samples. Final distances D between images i and j are computed as average of recto and verso distances. Fig. 2(left) shows the resulting affinity matrix, obtained setting ϵ to the standard deviation of distances between all pair of images. Sorted eigenvalues, and their successive differences reported in Fig. 2(middle) indicates that clustering with$K = 2$, 4 or 6 clusters are relevant. For ease of comparisons to photograph conservator grouping, $K = 4$ is retained here, and the corresponding dendrogram shown in Fig. 2(right). Robustness indices are reported in Fig. 3, averaged across 20 different noise levels.

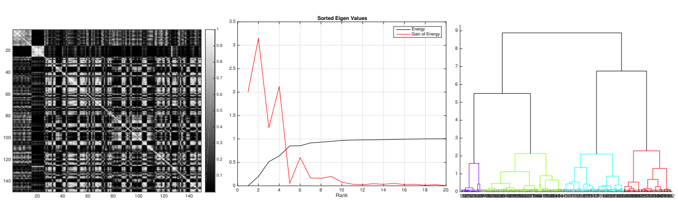

FIGURE 2 – **F. Holland. Day's Photograph paper clustering.** Affinity matrix (left). Spectral clustering sorted eigen values (middle). Dendrogram (right).

5.2 Photograph conservator grouping

Table 1, that compares the four clusters obtained using HWT features (hereafter clusters) to the nine groups obtained by photograph conservators (hereafter groups), permitted constructive discussions between image processing teams and photograph conservators.

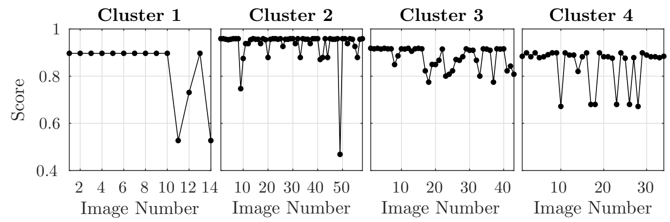

FIGURE 3 – **Robustness indices for each image per cluster.** F. Holland. Day's Photograph papers.

Table 1 shows an overall satisfactory agreement between clusters and groups, with clusters either globally matching Groups or gathering together several Groups. For instance, Cluster1 corresponds to GroupE, but for samples 267, 321, 513, 519. This is very satisfactory as photograph conservators indicated a posteriori that GroupE corresponds to *pebbly* textured papers that were used by a different artist (Frederick Evans), making copy prints of Day's work, at different time, and on different continent. Further, and interestingly, three of the four misclassified samples (267, 321 and 519) have low robustness indices (cf. Fig. 3), thus indicating a weak belonging to Cluster1.

Cluster 2 combines Groups F and S and some papers of Group A, and shows for each sample within that cluster high robustness indices, indicating a significant consistency of the cluster. This is confirmed by photograph conservators, who undertook a new visual inspection of papers in Groups A and S and agreed on significant visual similarities, with similar pebbled surfaces, except that S has a linear element. Also, papers from Groups A and S are used over a long period of time.

Table 1 also shows that some of the groups are split amongst different clusters. For instance, GroupB, that remained grouped together when a two cluster automated classification is achieved (not shown here), is split into Clusters 3 and 4. A new inspection of GroupB by the photograph conservators actually confirmed that samples from GroupB that fall into Cluster3 have smoother textures than those in Cluster4.

Photograph conservators also commented that Cluster3 is the less satisfactory as it gathers very different papers, from several Groups (K, M and Q) as well as some samples from Groups A and B. The lower consistency of Cluster3 is somehow indicated by robustness indices being globally lower for Cluster 3 than for the other clusters (cf. Fig 3), thus indicating less consistency for Cluster3. Photograph conservators, however, assessed that samples from Groups A and B gathered in Cluster3 are smoother that the other samples from Groups A and B. Also, Groups K and M, though different, consists of smooth papers. Cluster3 thus shows global consistency in gathering smooth textures. Group Q consists of a single sample, with paper very different from the rest of the collection. With respect to clustering, it thus consists of an outlier that the spectral clustering based ascendant (Ward linkage) classification used here is not equipped to handle. However and interestingly, its robustness index is the

	HWT cluster 1	HWT cluster 2	HWT cluster 3	HWT cluster 4
Group A	513, 519,	268, 278, 338, 376, 379, 480, 481, 483, 499, 500, 503, 504, 508, 509, 520, 649, 659, 660, 662, 665, 674, 675, 677,	246, 380, 386, 393, 501, 507, 651, 666,	280, 372,
Group B			131, 142, 319, 323, 325, 359, 364, 367, 371, 490, 492, 497, 498, 502, 521, 648,	255, 259, 260, 264, 265, 270, 279, 336, 368, 374, 375, 383, 389, 390, 392, 395, 396, 475, 488, 495, 506, 511, 645, 655, 656, 657, 669,
Group E	147, 148, 149, 150, 151, 152, 153, 154, 155, 156,			
Group F		251, 257, 269, 271, 378, 476, 522,		261,
Group H			317, 361, 365,	385, 391, 486, 487,
Group K			120, 121, 122, 123, 124, 125, 128,	
Group M			130, 135, 137, 138, 139, 140,	
Group Q			339,	
Group S	267, 321,	249, 252, 253, 258, 272, 273, 274, 275, 276, 277, 281, 282, 312, 313, 316, 320, 324, 328, 329, 330, 331, 332, 360, 363, 387, 516, 517, 518,	250, 334,	

TABLE 1 – Comparisons of the 4 automated HWT Clusters to the 9 photograph conservators groups.

lowest of Cluster3, indicating a weak belonging to the cluster. This also provides a valuable example of the relevance of the proposed robustness index.

6 Conclusions and perspectives

The present work has shown that the clustering methodology for the classification of art photographic paper based on HWT texture representation and spectral clustering dimensionality reduction, proposed and assessed in [7, 2], permitted a classification of photos by F. Holland Day that made sense to photograph conservators and lead them to reconsider aspects of their grouping methodology.

Additionally, a noise-assisted robustness index was devised to quantify for each sample the strength of its belonging to the assigned cluster. The relevance of that index was assessed by several a posteriori comments by the photograph conservators.

The achieved automated clustering also triggered interactions between the image processing teams and the photograph conservators, a valuable outcome of the present work. For instance, the PC had performed a consolidation of of their own groupings to get to a manageable number of clusters that seemed practical and useful while still maintaining the most significant visual differences. Some of the distinctions recognized across consolidated groups are actually re-emerging in some of the automated clusters. This was notably observed in the splitting of Group A and into several clusters according to texture smoothness, or the combining of Group S with some of the papers in Group A.

Future works will aim towards two different directions. Assessing the robustness of the clustering in terms of both selecting the relevant number of clusters and of assessing how much a sample belongs to a cluster, needs to be further investigated. Elaborating on Table 1, creating an interactive and dynamical *dialog* platform to trigger a *virtuous circle* of feedbacks between *expert observers* and *automatic classifiers*, constitutes a critical challenge for successful interdisciplinary interactions and will be at the core of future developments.

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