

Re-presentations of Art Collections

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Abstract. The objective of this paper is to show how modern computer vision methods can be used to aid the art or book historian in analysing large digital art collections.

We make three contributions: first, we show that simple document processing methods in combination with accurate instance based retrieval methods can be used to automatically obtain all the illustrations from a collection of illustrated documents. Second, we show that image level descriptors can be used to automatically cluster collections of images based on their categories, and thereby represent a collection by its semantic content. Third, we show that instance matching can be used to identify illustrations from the same source, e.g. printed from the same woodblock, and thereby represent a collection in a manner suitable for temporal analysis of the printing process.

These contributions are demonstrated on a collection of illustrated English Ballad sheets.

1 Introduction

Art and book historians now have huge digital collections available for study [1, 2]. This offers an opportunity and a problem: subtle comparisons can potentially be carried out over far more data than was ever possible before, however, the manual analysis methods that have traditionally been used are simply inadequate for collections of this scale (or would take many years of effort by an art historian).

In this paper we show that standard computer vision methods are, fairly effortlessly, able to *re-present* images in art collections in a way that are suitable for manual analysis and to some extent, can automate some of this analysis. We consider two canonical problems: *semantic clustering* – re-presenting the data in clusters that are semantically related. This enables art historians to carry out longitudinal studies on how the depiction of a particular concept has changed over time; and *instance clustering* – re-presenting the data as clusters of exact copies. Analysis of exact copies is of interest in dating and time ordering collections.

We exemplify these two representations using a dataset of images of broadside ballad sheets [3]. These are cheap printed sheets containing lyrics of popular songs (ballads), and woodblock printed illustrations. The sheets were printed from the sixteenth until the early twentieth centuries. The dataset, described



Fig. 1: **Woodcut illustrations.** The pair of illustrations on the left appear to be the same at first sight, but are printed from two different woodblocks. The pair on the right are printed from the same block, but there are small differences due to wear and tear.

in section 2, contains around 900 ballad sheets with many different ‘concepts’ illustrated (such as ‘the devil’ or ‘death’ or ‘eating and drinking’). There are identical copies (printed from the same woodblock), near but not exact copies of woodblocks (so near but not exact illustrations, but semantically related) in which the differences in the features and the shapes of the illustrations are very subtle, and also different depictions of the same concept.

The task of matching the woodblocks presents many challenges – the large quantity of woodblocks and illustrations makes them very difficult to organise by hand, and a pair of illustrations such as Figures 1a and 1b that look identical to all but the most trained eye may in fact be from a close copy of a woodblock. Comparing illustrations from the same woodblock is no easier – small damages to the woodblock, such as a wormhole in Figure 1d that is not present in Figure 1c, are again not obvious to the eye. Such differences may be identified under close inspection when the set consists of a few images, but the task becomes completely infeasible in a set of thousands.

Paper outline: Section 3 describes how woodblock illustration regions can be determined automatically by first removing areas of text, based on their characteristic patterns, and then refined and verified by matching and comparing to regions of similar illustrations on other ballad sheets. Section 4 describes the semantic clustering where compact descriptors such as VLAD and GIST are utilised to compute similarities between the illustrations, and thereby cluster them into semantically similar groupings. Within each cluster of semantically similar images, further analysis based on exact instance matching (SIFT and spatial verification) is performed to find illustrations that come from the same woodblock (section 5). A number of features are generated from the difference between the images, and a Support Vector Machine (SVM) is trained to distinguish prints from the same block from those from a copy. Finally, differences exist even between prints from the same woodblock, many of which are the result of damage to the block. These visual damage cues can be used to find a temporal ordering of the sheets.

1.1 Related work

The evolution and temporal ordering of illustrations is of great interest to art historians and bibliographers [4]. Monroy *et al.* [5] suggests that differences in the local image features can be used to visualise the temporal order in which the images were produced – *e.g.* the more times an illustration is copied, the more details that might differ from the original. Furthermore, Monroy *et al.* [6] notes that even closely traced copies of an artwork contain geometric distortions, and suggests grouping of deformations to reveal details about the process of copying the artwork.

For woodcuts, Hedges [7] discusses the correlation between wormholes in the centuries-old printed art and the history of the prints. The wormholes take a distinctive shape – small and round holes, around 1.4 to 2.3 mm in diameter – hence they are easily identifiable as the cues of relative age. The wormholes are not the only cues that can be used to order the illustrations. Hedges [8] gives useful insights into the cues one might use to order the woodcut illustrations.

There has been previous work on using instance (specific object) matching methods for Ballad images. In Bergel *et al.* [9] an image matching tool was developed to provide immediate matches of regions of interest within a collection of Ballad images. This used the standard bag of visual words method of [10, 11]. The paper only considered matching though, and there was no investigation of automated clustering, which is the goal of this submission.

2 The Ballads dataset

Broadside ballads are cheap printed sheets carrying lyrics, illustrations and the names of popular tunes. They were sold, displayed, sung and read in the streets and alehouses of Britain from the 16th until the early 20th centuries [3, 9]. The dataset used here contains around 900 images of ballad sheets from four different collections. For some of the images, estimated print dates or date-ranges are given. No further description is provided with the photographed ballad sheets.

All of the images are photographed in a standard format as shown in Figure 2 – on black background, and with a ruler on one side to show the physical scale. The images are around 3K pixels on the longest dimension. Most of the ballad sheets contain around one to five woodcut illustrations. The woodblocks, which are of particular interest here, come in various sizes – the largest blocks are over 15cm along their longer dimension, whereas the smaller blocks can be around 3cm in width.

3 Automatic cropping of illustrations

In this section we outline the method of identifying and cropping candidate objects (woodblock illustrations) from images of the ballad sheets. There are two stages, first putative regions are obtained from areas that are *not* text on the sheet, second instance matching with other copies of the woodblock print with



Fig. 2: Photographs of broadside ballad sheets

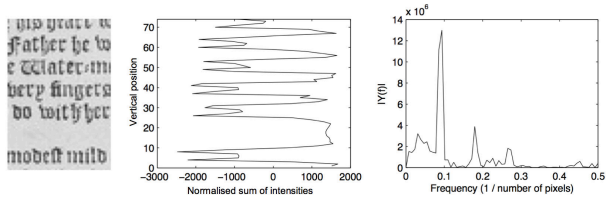
the collection is used to refine the regions and separate connected neighbouring objects into individual prints from different woodblocks.

3.1 Identifying text areas and candidate picture regions

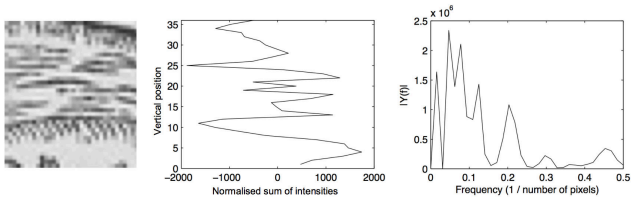
The main objects that appear in the broadside ballad sheets are text and pictures (woodblock illustrations). The vertical spacing of text is fairly regular – approximately 4 to 6 millimetres (8 to 12 pixels). As a result, if a horizontal sum of intensity values is taken over an area of text, it is possible to observe a regular pattern of intensities, as shown in Figure 3.

If a Fourier transform is taken over this signal, a sharp and distinctive peak is found at a frequency of around 0.1 (unit: per pixel), such as in the example shown in Figure 3a. However over any other area which does not contain text, no such peak is observed (Figure 3b). The process is repeated across the page with a moving window, and all areas showing a strong peak at such frequency are disregarded. Having removed the text, it is possible to search over the remaining area for candidate objects, given the known geometric constraints (for example, the illustrations must be greater than 3 cm in width and cannot lie on the page margin). The process is illustrated in figure 4.

Evaluation over a random set of 200 sheets shows good performance, with precision and recall of 98.5% and 99.1% respectively. There are examples where two neighbouring illustrations are erroneously proposed as one due to the illustrations being very close together. This is not considered an error at this point, and the problem is addressed in the following section.

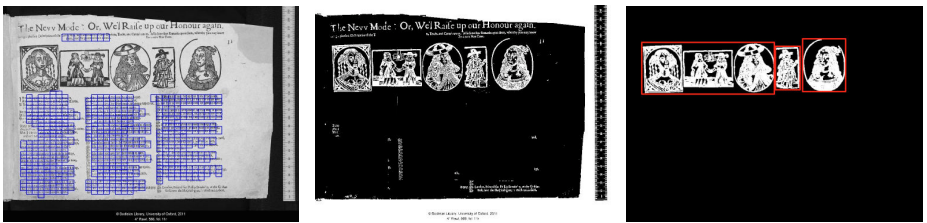


(a) An area of text – a distinctive peak is observed



(b) An area of image – no distinctive peak is observed

Fig. 3: Fourier transform of horizontal sum



(a) Regions of text

(b) Text removed from the binary image

(c) Bounding boxes detected

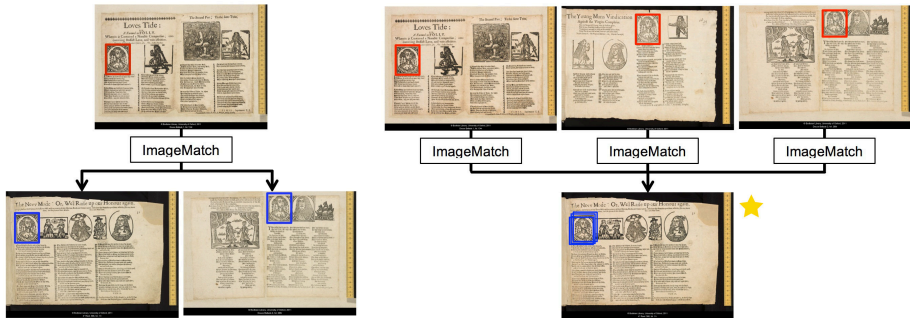
Fig. 4: Text detection and removal, and candidate bounding boxes.

3.2 Separation of connected neighbouring objects

At this point, some illustrations that are in very close proximity (typically within a few pixels of each other) are often highlighted as one connected component. In this section we resolve this problem using a local implementation of the standard BoW retrieval system [10] by searching over *all* putative regions. (For the retrieval system in detail, we use affine-Hessian interest points [12], a vocabulary of 100k vision words obtained using approximate k-means, and spatial re-ranking of the top 200 tf-idf results using an affine transformation).

Given a query illustration, the BoW system returns a ranked list of similar images containing the illustration and the estimated positions of the ROIs. For example, a query is generated from the image bound by the red rectangle in Figure 5a, which generates the blue rectangles that represent the estimated positions of similar images.

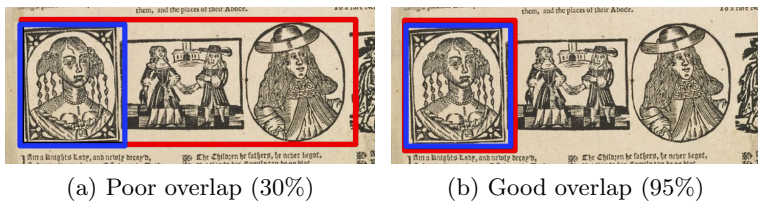
Now suppose that the queries are generated from many of the similar images as shown in Figure 5b. Each of the queries will give an estimated position of the matched image, which can be used as cues to determine the exact location.



(a) ImageMatch query from a single image

(b) ImageMatch query from multiple images

Fig. 5: Estimation of the image boundary using ImageMatch.



(a) Poor overlap (30%)

(b) Good overlap (95%)

Fig. 6: Overlap ratios between the original boundary (red) and the ImageMatch estimate (blue)

Figure 6a shows a subsection of the starred image in Figure 5b. In the figure, our original estimate of the image boundary is represented by the red rectangle. The blue rectangle represents an estimate given by an BoW ImageMatch query. The overlap ratio between the blue and the red rectangles are calculated. (The overlap ratio between areas A and B is defined as $\frac{A \cap B}{A \cup B}$.) In the example Figure 6a, the two rectangles show poor overlap (30%). The overlap ratios between the red rectangle and all of the other estimates are calculated, which mostly give poor ratios. This suggests a boundary refinement is necessary. However, if we suppose that the original image boundary is as shown in Figure 6b, the overlap ratio between the red rectangle and the BoW ImageMatch estimates would mostly show good overlap, which indicates that the original boundary is likely to be accurate.

The queries are generated from *all* of the illustrations detected in section 3.1, and the returned coordinates that overlap the ROI in question are noted as potential boundaries (Figure 7). This information is then used to cluster the boundaries of illustrations within the original candidate. First, the centre (x and y) and the size (height h and width w) of all blue boxes are calculated. Then, the boxes whose x and y values are furthest from the median are iteratively deleted until the standard deviation of the remaining boxes are within the threshold. The same is repeated for w and h values of the boxes that are not rejected in the previous step. The mean of the remaining boxes are taken as the new boundary.

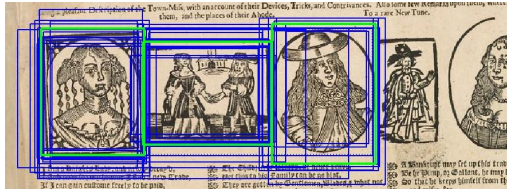


Fig. 7: **Separation of neighbouring illustrations.** Blue boxes show all potential boundaries generated using ImageMatch. Green boxes show final separation of the illustrations.

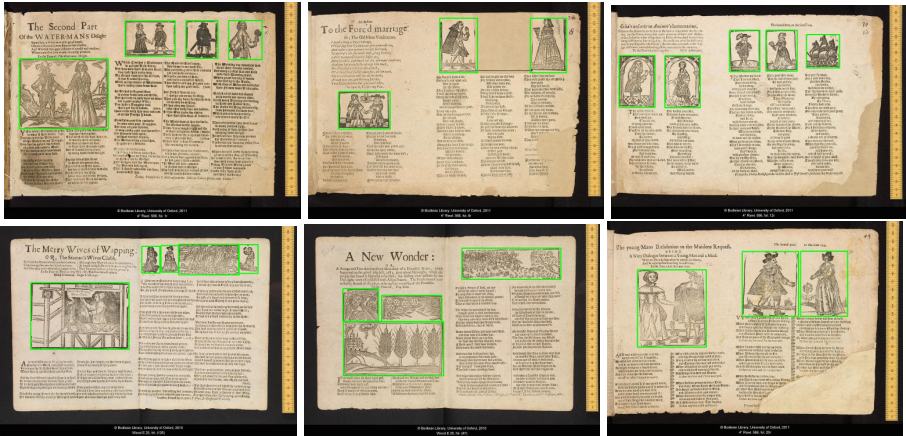


Fig. 8: Automatically detected boundaries of woodcut illustrations

Where the resultant boundary does not cover most of the initial object (over 80%), the process is repeated using the remaining, unused ROIs, until the process returns no more estimates that do not overlap the new objects.

The green rectangles in Figure 7 show the final cropping result on the example image used throughout this chapter. On a test set of 200 pages, the method proved to be reliable for all examples where the new boundary is defined by averaging three or more BoW ImageMatch returns. As this process relies on majority voting on the cropping data from Section 3.1, it is necessary that a large majority of the illustrations are already correctly cropped as in the example Figure 7.

From the full set of 900 broadside ballad sheets, around 2,600 individual illustrations are detected and cropped. Selected results are shown in Figure 8.

4 Semantically similar illustrations

Having identified the woodblock illustrations in section 3, the main objective of this section is to automatically find and cluster the illustrations that are semantically similar to each other. Note, to avoid confusion, we are not trying to assign illustrations to manually curated classes defined by cataloguers, such as the Iconclass [13] system.

Similarity of two illustrations is computed as a weighted sum of consistency between their aspect ratios and weighted similarities of three different image descriptors: VLAD, spatially pooled VLAD and GIST; which are described next.

GIST. The GIST [14] image descriptor provides a holistic description of the scene, capturing coarse image gradients, where local object information is not taken into account. Similarity of two illustrations is computed as the negative L2-distance between their GIST descriptors. While providing a good descriptor for the overall shape of a scene, GIST can be sensitive to cropping [15].

VLAD. The Vector of Locally Aggregated Descriptors (VLAD) [16] summarizes the distribution of local SIFT [17] descriptors in an image. It has gained popularity due to good performance in image retrieval tasks [18, 19, 20, 21] while providing a compact image descriptor. Similarity between two illustrations is computed as the scalar product between their VLAD encodings.

Spatially pooled VLAD. Since VLAD does not encode any spatial information, we also compute VLAD for five predefined spatial tiles each spanning a quarter of the image area. The pooling regions are the four quadrants of the image and a region of equal size in the centre of the image. The similarity between two illustrations is computed as the weighted sum of scalar product between the spatially pooled VLAD's.

The weights are tuned manually over a small number of clusters and concepts, and then used for all further comparisons.

4.1 Clustering similar illustrations

Similarity is computed between all pairs of illustrations, which can be done efficiently due to using compact GIST and VLAD descriptors. For larger datasets, this step can be performed by approximate nearest neighbour search [22] or fast memory-efficient search by quantizing the descriptors [23]. The pairwise similarities are thresholded and a graph is formed such that nodes correspond to illustrations and undirected edges connect nodes of sufficient semantic similarity. Clustering is then performed by extracting connected components from the similarity graph. We then refine clusters with large intra-cluster variability to alleviate cases where a weak erroneous link between two different clusters causes undersegmentation. The refinement is performed by identifying clusters with large variance of intra-cluster similarities, and removing edges by enforcing a stricter similarity threshold, followed by recomputation of connected components. Some of the automatically obtained clusters are shown in figure 9.

5 Identifying illustrations printed from the same woodblock

The objective of this section is to automatically identify prints generated from the same woodblock. This is of particular interest to cataloguers and art historians as tracking the use of a woodblock provides insights into the origin of the



Fig. 9: Semantically similar images automatically detected and clustered

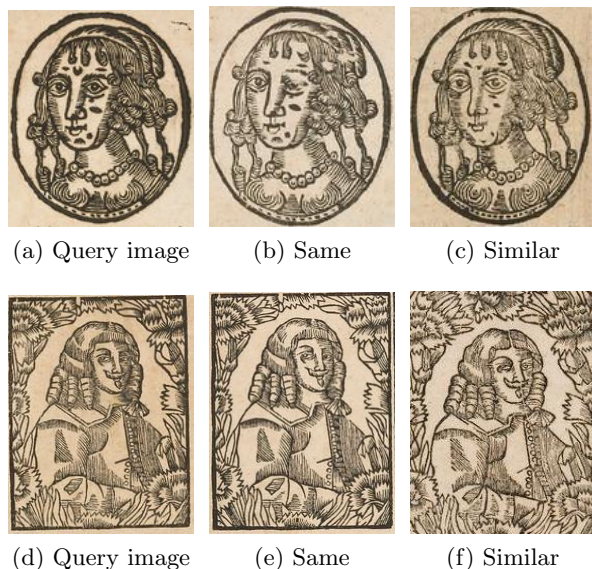


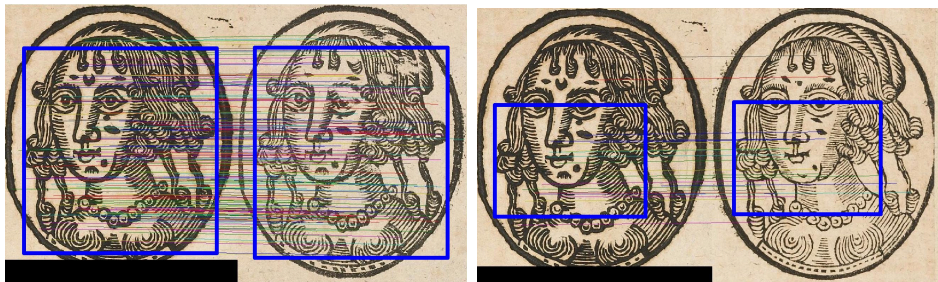
Fig.10: **Same vs similar pairs.** In each row, the first two illustrations are printed from the same woodblock. The last illustration appears to be very similar, but comes from a different woodblock that is a copy of the original block.

printed material, such as the identity of the printer, the place of printing, or the sale or loan of a woodblock providing information about relationships between printers. Moreover, examining the changes in the condition of a woodblock, such as the development of wormholes, allows for automatic dating of the sheets [7, 8].

Section 4 described a method for mining clusters containing similar illustrations, here we concentrate on finer clustering to only group illustrations printed from the same woodblock. Therefore, we examine all pairs of illustrations in a semantic cluster to determine if they come from the same woodblock. This is a challenging task as it was common practice to closely copy woodblocks therefore giving rise to sets of very similar illustrations (figure 10).

A linear SVM is trained to distinguish between a pair of *same* (i.e. printed from the same woodblock) and *similar* (i.e. printed from a similar and likely copied woodblock) illustrations, using features which assess geometric consistency of the illustrations. The use of geometry is motivated by the observation that, even though two similar illustrations look quite well aligned, it is unlikely that they are related with a very accurate global rigid transformation as a result of the geometrical errors accumulated during the copying process [5]. The geometry-based features are discussed next.

An affine transformation which aligns one illustration with the other is automatically estimated by forming a set of putative correspondences by matching SIFT [17] descriptors using the second nearest neighbour test [17], and finding the affine transformation which explains the largest number of the putative correspondences using RANSAC [24]. Features which help determine the quality of the affine transformation are: i) the number of putative SIFT-based matches



(a) Inliers in a same pair

(b) Inliers in a similar pair

Fig. 11: **Spatial distribution of inliers.** Lines connect SIFT descriptors consistent with an affine transformation. The blue rectangles show the bounding boxes of spatially consistent descriptors.

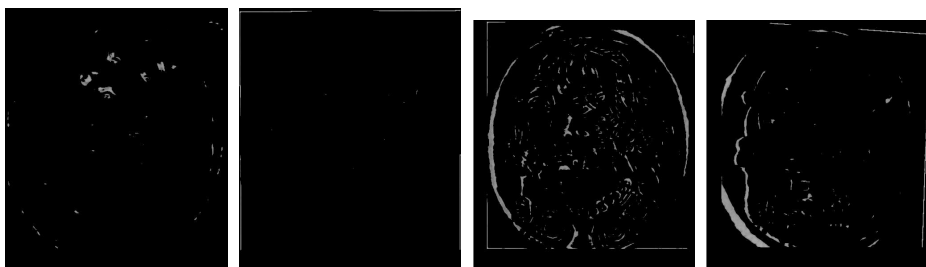
(a) $I_{1,2}$ (Same)(b) $I_{2,1}$ (Same)(c) $I_{1,2}$ (Similar)(d) $I_{2,1}$ (Similar)

Fig. 12: Difference images for illustrations from same and similar woodblocks

(n_p); ii) the ratio of number of matches spatially consistent with the best affine transformation, n_s , and n_p (n_s/n_p); and iii) the density of matches (n_s divided by illustration size).

We also observe that the spatial distribution of spatially consistent features is informative (figure 11) – a same pair has features matching across the entire illustration, while a similar pair often has only locally consistent matches. The spatial spread is measured as the proportion of the illustration area covered by the bounding box of spatially matched features. The bounding box is computed as the smallest axis aligned rectangle which contains the central 90% of features; this procedure ensures robustness by eliminating spurious matches which could affect the bounding box estimation.

Finally, we also include two features which capture fine level differences between the two illustrations. Let I_1 and I_2 be a pair of illustrations such that I_2 is automatically registered to I_1 using the aforementioned affine transformation, and both are binarized to 1 and 0 to indicate pixels which contain and don't contain ink, respectively. From these, one can compute binary difference images $I_{i,j}$ which indicate pixels where image I_i contains ink and image I_j does not. As can be seen from figure 12, the difference images $I_{1,2}$ and $I_{2,1}$ can help discriminate between same and similar pairs of illustrations. This is because for a same pair, in an ideal scenario, an $I_{i,j}$ image will be completely empty (figure 12b)

Table 1: Performance of same vs similar classification.

	Precision	Recall	Precision	Recall
ImageMatch	78%	80%	69%	90%
RANSAC statistics	98%	80%	95%	90%
Our method	100%	80%	100%	90%

signifying that j was printed after i as all ink in I_j is present in I_i , i.e. ink could have only disappeared from I_i to I_j corresponding to potential damages to the woodblock (the disappeared ink is visible in image $I_{j,i}$, figure 12a). On the other hand, similar (not same) pairs have much less sparse $I_{i,j}$'s (figures 12c and 12d).

Let $|I_{i,j}|$ denote the number of ones in the difference image $I_{i,j}$, and without loss of generality let $I_{2,1}$ be the sparser image (i.e. $|I_{2,1}| \leq |I_{1,2}|$). The two features which summarize the above observations are $p_{min} = |I_{2,1}|/A$ and $p_{max} = |I_{1,2}|/A$, where A is the illustration area. Therefore, p_{min} is close to zero for same pairs (figure 12b) and large for similar pairs (figure 12d), while p_{max} also contains useful information as it should be smaller for same pairs compared to similar ones (figure 12a vs 12c). In practice, we first perform image opening with a small radius on images $I_{i,j}$ in order to remove the differences in the thickness of lines caused by varying amounts of ink on the woodblock.

To summarize, six features are used for classification into same versus similar illustration pairs – three capturing the counts and relative counts of putative and spatially consistent descriptor matches, one measuring the spatial distribution of spatially consistent matches, and two capturing pixel-wise differences in inking.

5.1 Evaluation procedure and results

Benchmark dataset. To evaluate the classification accuracy of the proposed method, we have manually labelled a random sample of 150 pairs of illustrations obtained from clusters in section 4, such that there is a roughly equal number of same vs similar pairs. This set was divided into 50% for training, 25% for validation and 25% for testing.

Baselines. We compare the proposed approach with two baselines. The first is a classifier based purely on the number of spatially verified matches obtained from ImageMatch (section 3.2), namely a pair of illustrations is deemed to be a same match if the number of matches in ImageMatch is larger than a threshold. The second is an SVM classifier trained only on the first three features of our method which capture the RANSAC-based statistics, i.e. n_p , n_s/n_p , and density of n_s .

Results. Table 1 shows the results of our method compared to the two baselines. It can be seen that ImageMatch is not as good as the other two methods as it only uses match count as a feature, as well as due to quantizing descriptors into visual words. The RANSAC statistics performs quite well, but our method which uses all six features significantly outperforms it, simultaneously achieving higher



Fig. 13: **Clustering example.** For the running example images our method finds two clusters, shown one per row.

recall and precision, namely, our method gets 100% precision at 90% recall while RANSAC statistics achieves 98% precision at 80% recall, and only 95% precision and 90% recall.

We pick the operating point which achieves maximal recall for 100% precision (recall at this point is 90%) and cluster together illustrations which are deemed to be same matches. The final results on the running example are shown in figure 13, while figure 14 shows some further examples.

5.2 Application: Temporal ordering of the illustrations

The likely printer of a sheet can be identified if his identity is known for a sheet which shares an illustration belonging to the same cluster. In similar ways, one can also determine the place of printing or relationships between printers [25].

One interesting application is to automatically date a sheet – two sheets which contain an illustration printed from the same woodblock can be ordered temporally by examining fine-level changes in the impressions. This application is beyond the scope of this paper, but we give a brief sketch of the method. For example, from figures 12a and 12b, it is evident that illustration I_2 contains less ink than I_1 (as $I_{2,1}$, figure 12b, is empty) due to degradations of the woodblock (locations of which are apparent in $I_{1,2}$, figure 12a). Therefore, in this example it can be concluded that I_2 has been printed later than I_1 . Using such automatically discovered temporal constraints¹, it is easy to order many sheets in terms of their printing time. As dates of certain sheets are known, the temporal ordering can help narrow down the printing date of other sheets. Using this logic, it was possible to automatically assign dates or date-ranges to over 70 ballad sheets whose print dates were previously unknown.

¹ Actually we have a more robust method than simply measuring the amount of ink difference in $I_{i,j}$, but it is beyond the scope of this paper



Fig. 14: Illustrations from the same woodblock automatically detected and clustered

6 Discussion

The three contributions of this paper: automatic cropping of illustrations, semantic clustering, and exact clustering (with applications to temporal ordering) have general applicability. For example, the cropping method could be applied to any collection that mixes text and repeated illustrations. The two types of clustering can be applied to any collection with some commonality in illustrations, e.g. those printed from woodblocks, such as medieval incunabula (e.g. ‘The Book of Hours’), or collections with illustrations printed using engravings or lithography. All of these cases have the three aspects of illustrations from the same source, near copies and different depictions of concepts.

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