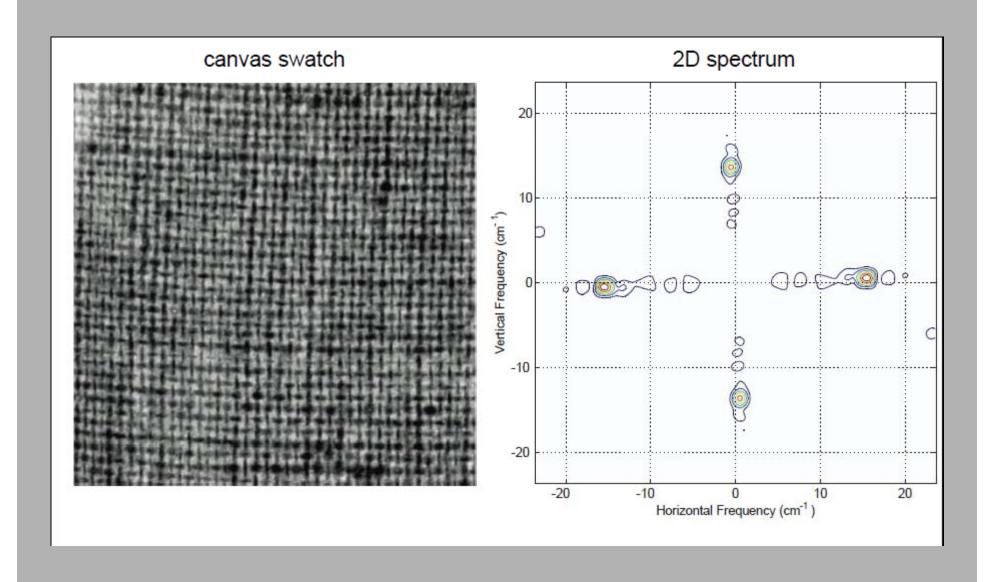
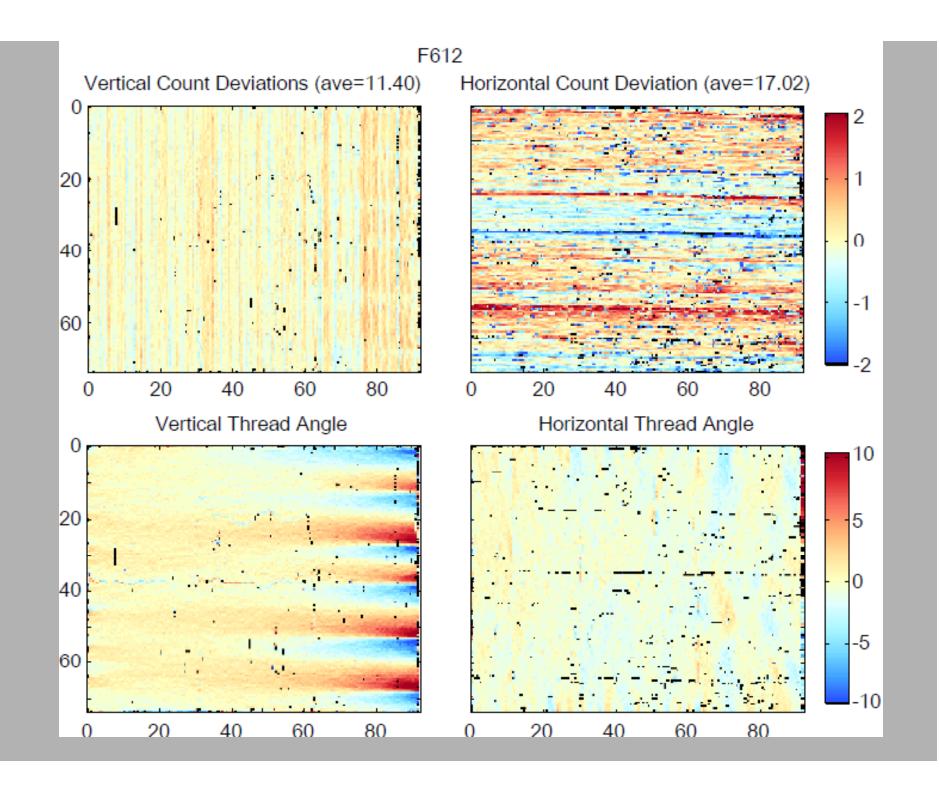


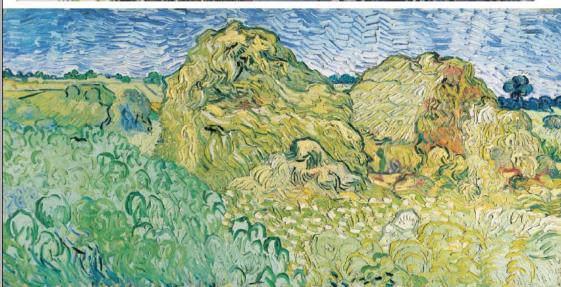
As the intensity pattern is roughly periodic its Fourier series composition can be expected to have a strong term that corresponds to the average period of this particular signal. For a set of sampled data, the Discrete Fourier Transform (DFT)<sup>9</sup> can be used to numerically determine the strengths of sinusoidal components of the data across a range of frequencies. In June 2007, this realization spawned a simple semi-automated procedure involving the following steps:

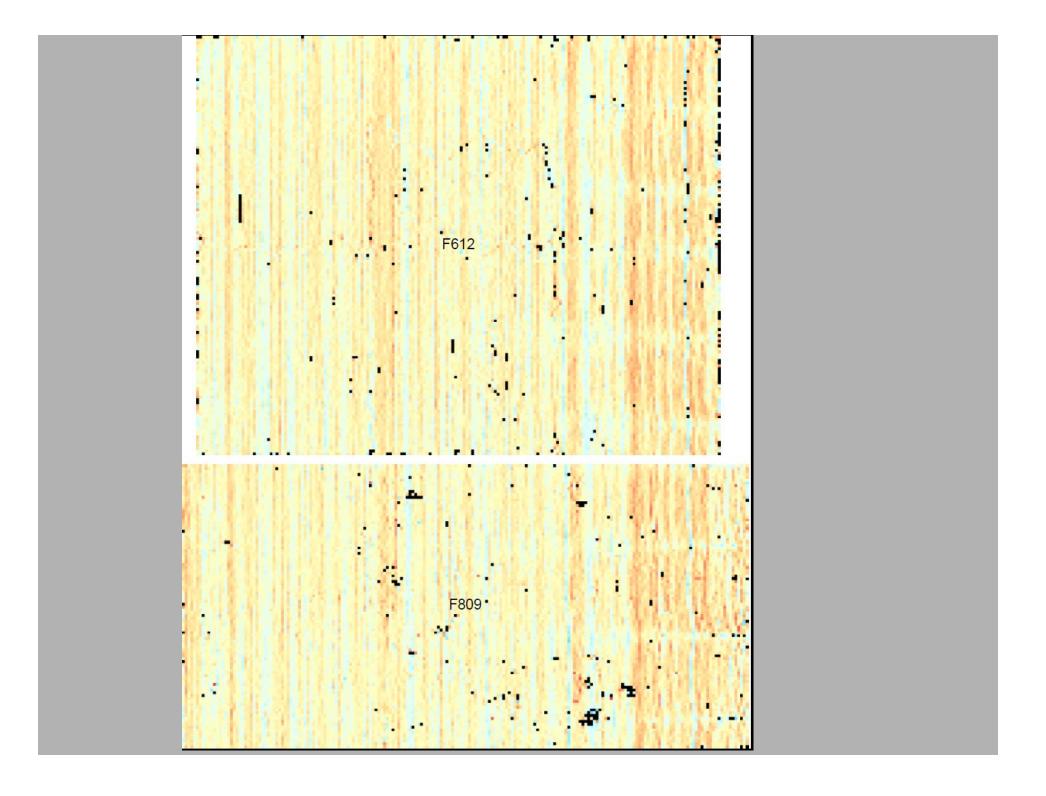
- Draw horizontal/vertical line across scanned x-ray image.
- Compute discrete Fourier transform (DFT) of horizontal/vertical intensity curve.
- Ascertain frequency location within suitable range of DFT magnitude maximum.
- Convert to threads/cm.

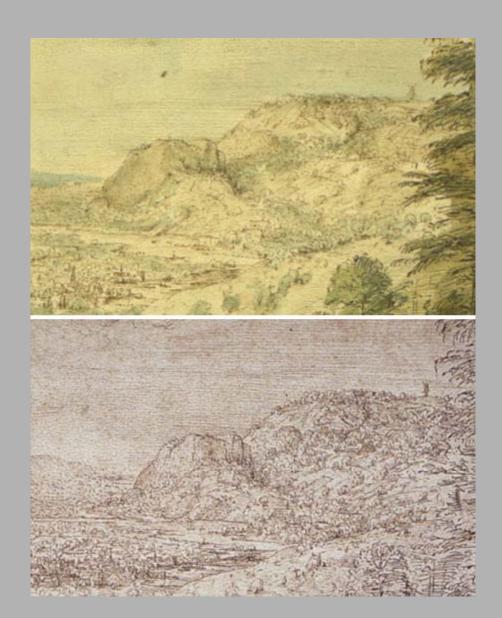












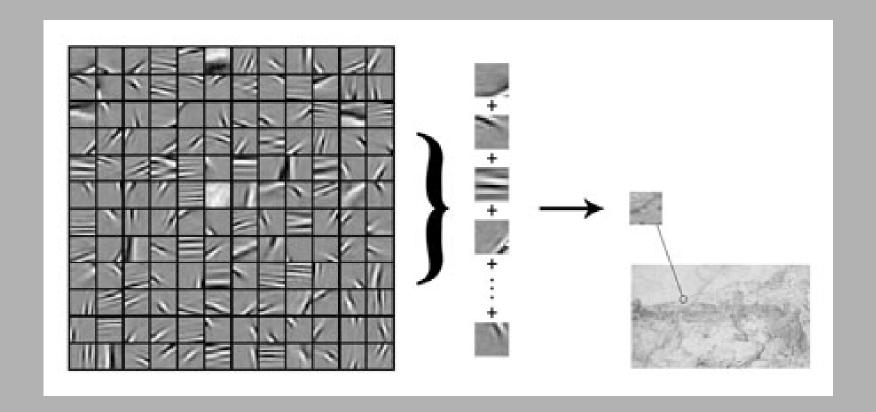






Figure 2: Two devices for collecting PTMs.

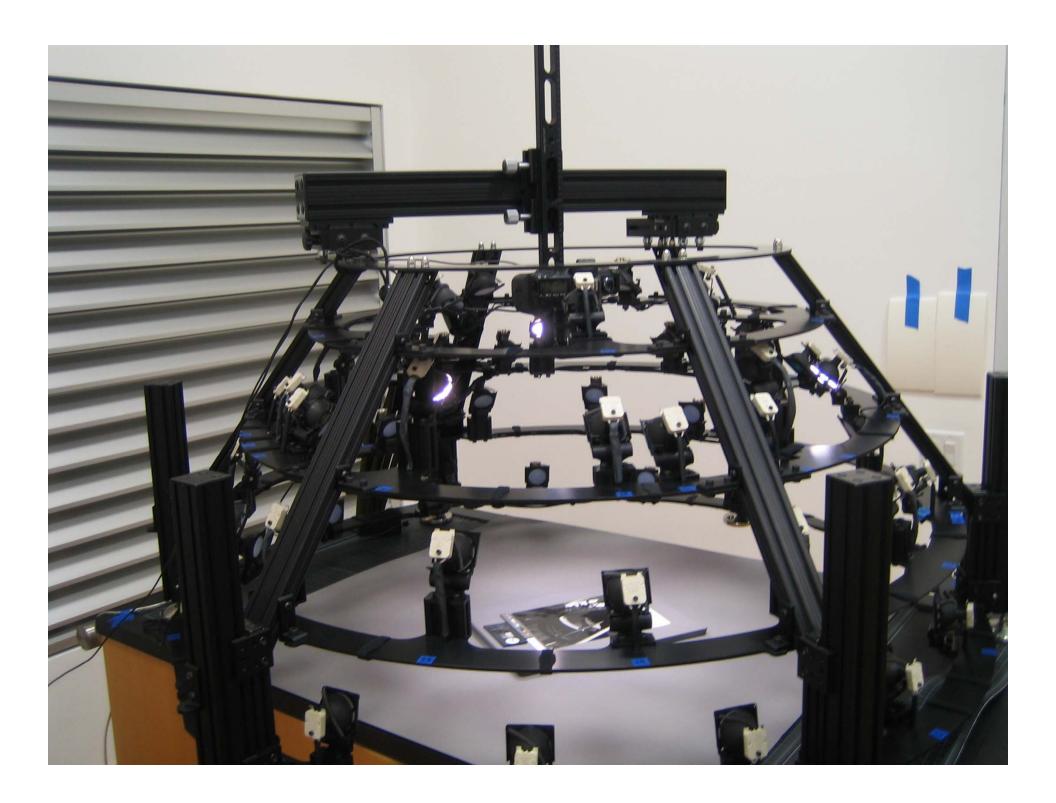
Although very simple, this method is capable of achieving good results, such as the archeological samples shown later in the paper. The second device allows fully automated acquisition of 50 source images, each illuminated with an individual strobe light source. In both cases the camera (not shown) is mounted in the

$$L(u,v;l_u,l_v) = a_0(u,v)l_u^2 + a_1(u,v)l_v^2 + a_2(u,v)l_ul_v + a_3(u,v)l_u + a_4(u,v)l_v + a_5(u,v)$$
(5)

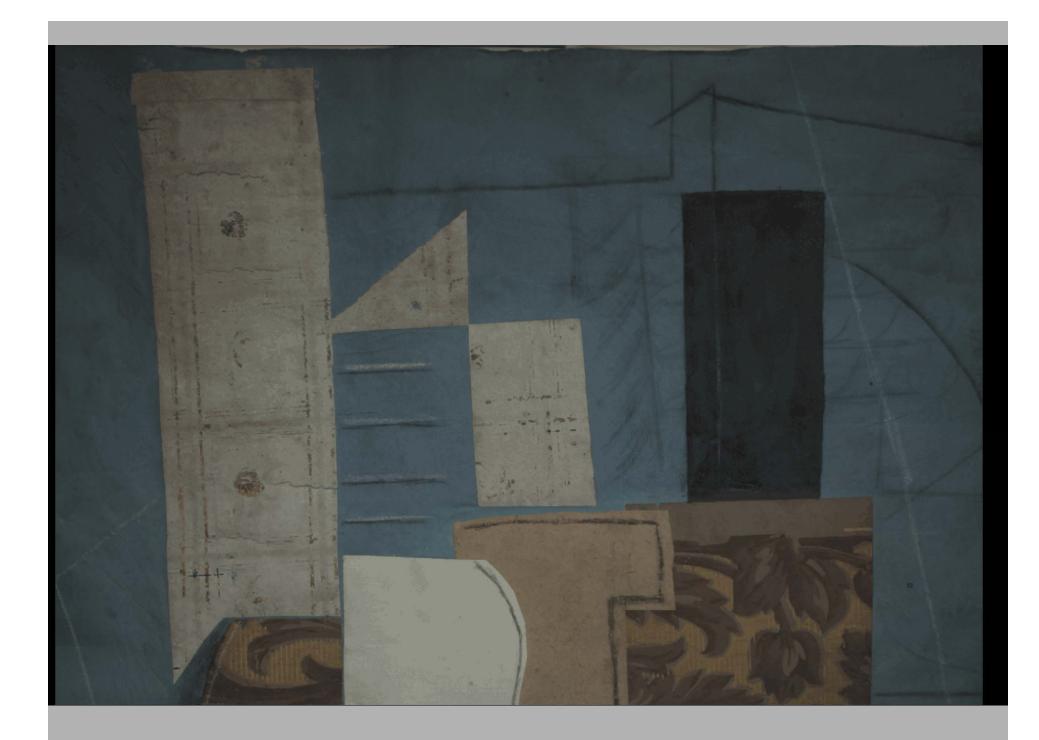
where  $(l_w l_v)$  are projections of the normalized light vector into the local texture coordinate system (u,v) and L is the resultant surface luminance at that coordinate. The local coordinate system is defined per vertex, based on the normal and on the tangent and binormal derived from the local texture coordinates. Coefficients  $(a_0-a_5)$  are fit to the photographic data per texel and stored as a spatial map referred to as a Polynomial Texture Map. Given N+1 images, for each pixel we compute the best fit in the  $L_2$  norm using singular value decomposition (SVD) [Golub 89] to solve the following system of equations for  $a_0-a_5$ .

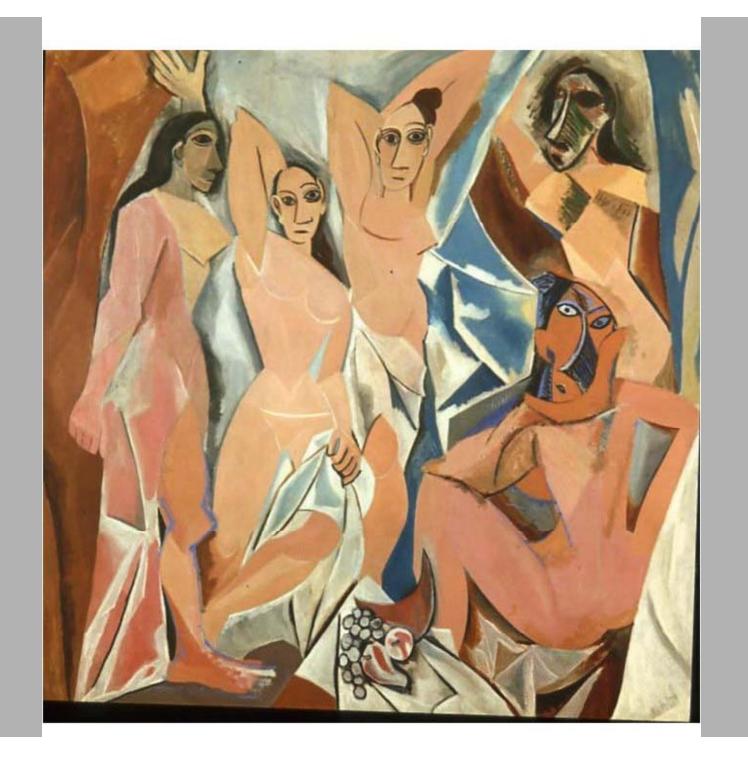
$$\begin{bmatrix} l_{u0}^{2} & l_{v0}^{2} & l_{u0}l_{v0} & l_{u0} & l_{v0} & 1\\ l_{u1}^{2} & l_{v1}^{2} & l_{u1}l_{v1} & l_{u1} & l_{v1} & 1\\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots\\ l_{uN}^{2} & l_{vN}^{2} & l_{uN}l_{vN} & l_{uN} & l_{vN} & 1 \end{bmatrix} \begin{bmatrix} a_{0} \\ a_{1} \\ \vdots \\ a_{5} \end{bmatrix} = \begin{bmatrix} L_{0} \\ L_{1} \\ \vdots \\ L_{N} \end{bmatrix}$$
(6)

Note that the SVD needs to be computed only once given an arrangement of light sources and then can be applied per pixel. The quadratic model proposed in Eq. 5 provides only an approximate fit to the observed color values. Note however that the resultant smoothing that occurs due to this approximation manifests itself only across the space of light directions and does not introduce any spatial blurring. This light space smoothing can have the effect of muting sharp specularities, softening hard shadows and essentially changing point light sources to area lights. However, arbitrarily high spatial frequencies in the original source photographs are preserved. Furthermore, we have verified that the general shape of the function described by the input data is well preserved. We have computed the root mean square error over all the pixels, and obtained a maximum error of roughly 10 per 8-bit color channel for typical examples such as the seeds













## Paint vs Ground Reflectance Ratios

