An interactive method for adaptive acquisition in Reflectance Transformation Imaging for cultural heritage

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Abstract

This paper investigates the optimization of acquisition in Reflectance Transformation Imaging (RTI). Current methods for RTI acquisition are either computationally expensive or impractical, which leads to continued reliance on conventional classical methods like homogenous equally spaced methods in museums. We propose a methodology that is aimed at dynamic collaboration between automated analysis and cultural heritage expert knowledge to obtain optimized light positions. Our approach is cost-effective and adaptive to both linear and non-linear reflectance profile scenarios. The practical contribution of research in this field has a considerable impact on the cultural heritage context and beyond.

1. Introduction

Reflectance Transformation Imaging (RTI) is an imaging technique used to enhance the visualization experience. It is a non-contact, non-destructive technique which makes it particularly interesting for cultural heritage applications.

The RTI principle encompasses three main stages. The first step is known as Acquisition which involves hardware components *e.g.* robotic arms or servo motors in conjunction with software algorithms to facilitate the acquisition. It also involves designing light sources and choice of suitable light and its compatibility with the camera. This step of acquisition results in capturing a sequence of images under different light positions. The diversity of light directions is crucial for revealing the surface details. The RTI acquisition setup primarily consists of a camera, light source, and object that is to be captured. It is demonstrated in figure 1.

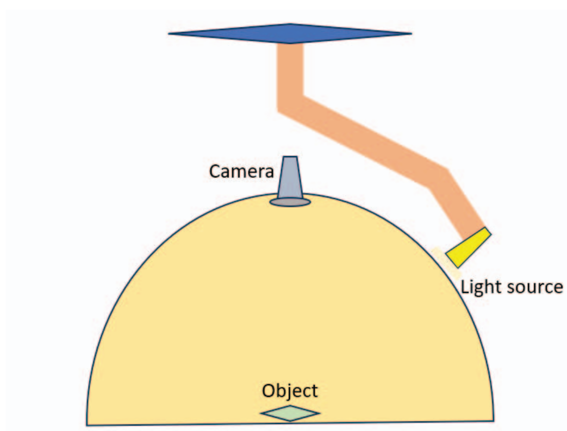


Figure 1: Reflectance Transformation Imaging (RTI) Setup. The camera and object are fixed whereas the light source is moving for every acquisition.

After performing acquisition on RTI setup, the resulting data is known as RTI data. However, it is worth mentioning that it is also known by other names like Multi Light Image Collection (MLIC), Single Camera Multi Light (SCML), and Multi Light Reflectance (MLR). These alternative names are used by different researchers and practitioners in different contexts however they all refer to the same concept of acquiring the data from RTI [41].

The second step in RTI process is referred to as modeling. This is the core of RTI. These are algorithms that use RTI images to learn the ability to understand the surface. The oldest and first method was Polynomial Texture Mapping (PTM) [25] in which the author developed a re-lightening algorithm. It interactively displayed the rendered images from light positions that were not captured physically during RTI acquisition. Subsequently, some other modeling methods were developed as advancements in the field. The notable ones are Hemi-Spherical Harmonics (HSH) [13, 40], Discrete Modal Decomposition (DMD) [32] and NeuralRTI [9]. The modeling algorithms can also be used for learning features of an object such as Normal maps, directional slopes, enhancement maps, directional curvatures, etc.

The third and final step of RTI is known as feature extraction. The feature maps serve as valuable tools for conducting meaningful tasks like investigating cultural heritage objects, studying deterioration in the artifact, or digitizing the cultural heritage object.

RTI allows visualization and exploration of an object's texture, shape, and other properties of the object revealing hidden details and aiding in the analysis, interpretation, and preservation of objects of archeological or cultural interest. RTI is used to study degradation in paintings and artifacts over time which makes it a paramount imaging technique for archaeological and cultural heritage investigations [37, 24, 38, 34, 30, 10, 26]. RTI also provides visual analysis, conservation documentation, and monitoring of remedial operations in cultural heritage [20, 11, 24, 39, 35, 15, 27].

RTI's integration with other imaging modalities has demonstrated profound utility in the domain of cultural heritage. A significant advancement in RTI is the incorporation of High Dynamic Range Reflectance Transformation Imaging (HDR-RTI)[29], Multi-Spectral Reflectance Transformation Imaging (MS-RTI)[18, 14, 2], Florescence Transformation Imaging (FTI) [5, 19] and Focus Variation Reflectance Transformation Imaging [21] techniques in it. These techniques provide better opportunities for surface analysis bringing new knowledge to the field of cultural heritage and archeology. However, these enhanced capabilities demand substantial data acquisition and processing, giving rise to computational challenges. An efficient data acquisition methodology aimed at ameliorating the computational burdens and bringing optimal efficiency within the domain of RTI is a need of the hour.

There are also different RTI acquisition methods that have been used and developed over the years. The basic one is Highlight-RTI (H-RTI) [28] in which the camera is on a tripod and acquisition is carried out with a handheld light source. However handheld acquisition is a painstaking and tedious task prompting the development of machine setups to bring efficiency and precision to the acquisition process. One of them is the called Fixed Light Dome [17]. It has fixed light sources attached to the dome body numbering from 40 to 100 but provides less liberty in the choice of light position. However, since the LEDs are fixed and there is no moving part, it is fast. Another one is known as Mechanized Dome System. It consists of a servo motor that moves the light source inside the dome [42, 16]. Recently, robotic arm-based systems have been developed to capture large surfaces for RTI [22, 18].

The choice of light positions is one important part of acquisitions. There are two categories for classifying the selection of light positions for RTI acquisitions. The first category encompasses pre-defined light positions. An example of this category would be evenly spaced light positions. The number and position of the light is pre-defined without any consideration of the surface of the object. The goal is to capture as much of the surface as possible. This principle of acquisition supposes that all light positions contribute equally. However, it is observed that surface reflectance is a complicated phenomenon and some light positions have more importance than others. In contrast, the second category employs automated methods which have the ability to adjust the number and distribution of light positions based on the surface characteristics. However, the field of automated acquisition is not fully explored. Our objective is to delve into the field of automated acquisition by leveraging surface information.

It is important to understand the significance of an optimized acquisition algorithm for RTI. RTI is an imaging technique that is centered around processing multiple, often high-quality images (Multi Light Image Collection). This demands very high computational power which often causes a bottleneck in the RTI pipeline. The quality of RTI results is generally enhanced by increasing the number of light positions however it is an important tradeoff between a high-quality reflectance modal resulting from a larger number of light positions and associated resources to acquire them. The intricacies and irregularities of an object's surface pose a formidable challenge in identifying the optimal lighting angles for RTI acquisition. Cultural heritage objects are complicated surfaces offering multiplicity in reflectance profiles and topography traits, offering unique textures, thus rendering each region on the surface as a distinct entity. It is found that cultural heritage professionals often prioritize specific regions of interest over the entirety of a given surface. Furthermore, optimizing these regions of interest yields significant benefits thereby contributing to the preservation, examination, and digitization of cultural heritage objects.

In this paper, we present a surface adaptive method for the planning of light positions for RTI based on the Region of Interest (ROI) selected by an expert and propose new surface adaptive light positions to the expert. The method is based on the analysis of sparse RTI data and finds optimal light positions using gradients. The method also provides the cultural heritage expert the liberty of interacting with the algorithm to produce the new light positions thus taking leverage of human and technological expertise. Cultural heritage professionals possess a profound understanding of the intricacies and complexities inherent in various objects. Our tool can provide them an opportunity to interact, focus and identify the best light positions for the acquisition. We leverage expert knowledge and technical analysis tools to collaborate for optimizing acquisition.

The section 2 discusses the related work in this field. Section 3 explains the methodology. Section 4 presents the dataset, experimentation, and results. Finally, section 5 discusses the conclusion of this study.

2. Related Work

The field of automated RTI acquisition is not fully explored. Initially, the tedious acquisition for RTI prompted the cultural heritage workers to find better ways to acquire data. One of the conservators came up with the trial and error method for refining the light positions after a predefined homogenous equally spaced acquisition [1]. The nearest work related to our work is Next Best Light Position (NBLP) [23]. In this work, the author first acquires a small sparse dataset, investigates reflectance changes in the dataset, and proposes the next best light position. However, the method is computationally expensive and thus is hard to implement practically.

Photometric Stereo serves as a closely related field to RTI. There has been some work to find the optimal light positions for Photometric stereo [8, 12, 4, 3]. Another inspiring but distinct to RTI acquisition problem is Next Best View (NBV) problem for 3D reconstruction where they develop planning algorithms for future acquisitions that can potentially give promising 3D reconstruction results [6, 36, 7, 31].

3. Methodology

The aim of this research is to improve the acquisition part of RTI. This research involves the optimized placement of light positions adapting to the surface. The primary objective is to maximize the information extracted from RTI data while minimizing the number of required images. Our methodology is based on Signal analysis. The figure 6 and figure 4 demonstrates the method.

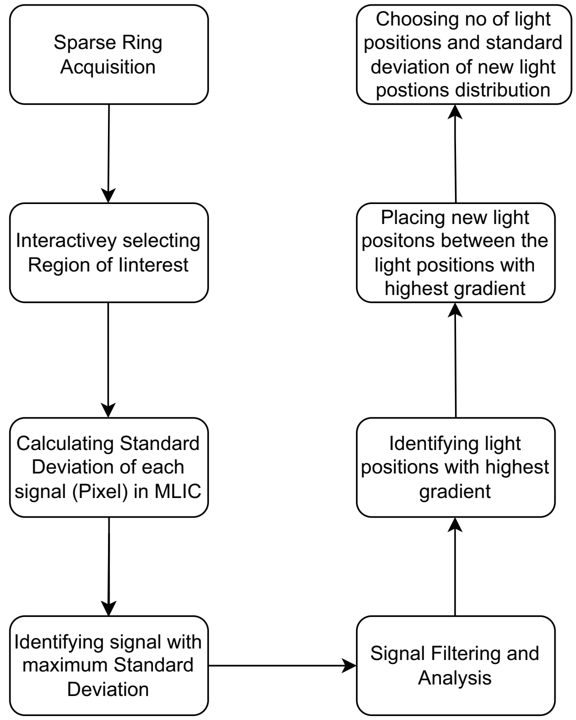


Figure 2: Flowchart of our method

The first step is to take a sparse acquisition. Our method is designed to optimize the acquisition in ring setup. We choose ring setup because the variation in pixel intensity through ring setup (varying azimuth, fixed elevation) manifests a non-linear and unpredictable pattern. Such responses are highly dependable on surface characteristics thereby presenting a significant challenge for modeling. Notwithstanding, maintaining a fixed azimuth and modulating the elevation demonstrates a more predictable response that can be modeled relatively easily. Figure 3 describes the elevation and azimuth angle for the RTI setup.

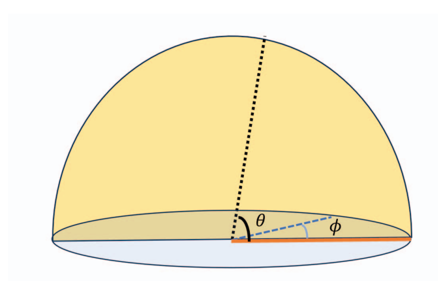


Figure 3: The figure demonstrates elevation (θ) and azimuth (ϕ) angle for acquisition setup.

We provide an interactive way to choose the Region of

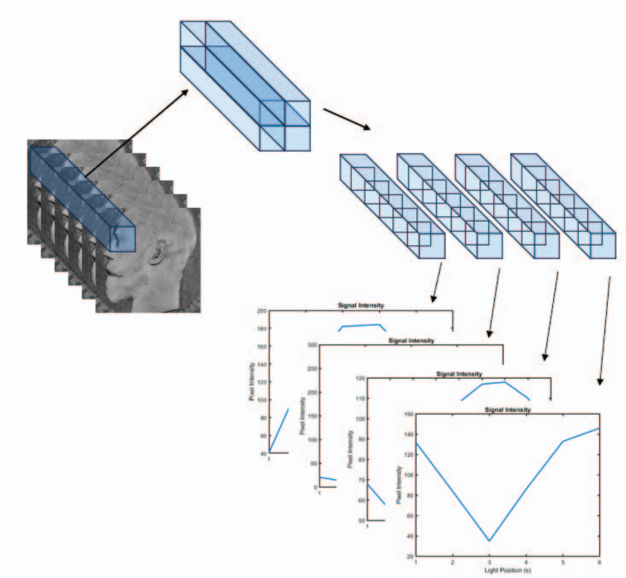


Figure 4: The figure demonstrates the data selection of our method. In the first step, the user interactively selects the region of interest. The ROI consists of a certain number of pixels. The pixel value is extracted all along the MLIC to form a signal. Each signal is then examined and signal analysis techniques are applied to find the Pixel of Interest.

Interest (ROI). The ROI can be chosen by a cultural heritage expert (user) for *e.g*. it can be a region where there is a specularity or a surface with irregular reflectance. The choice of ROI narrows down the location and significantly reduces the computational power. The algorithm creates a mask of the ROI and analyzes every pixel in the dataset. We perform some signal filtering if needed. Signal filtering involves using a low-pass filter. It can reduce sensor noise, and smoothen the signal. We then identify the pixel with the highest standard deviation in the dataset. Note that each pixel vector is a signal. We name this pixel as Pixel of Interest (POI). We calculate the gradient of POI in the dataset and find out the light positions where there is the highest gradient. The importance of POI is demonstrated in figure 5. The light positions with the highest gradient deduce that there is some latent information that has to be captured. In order to reveal that information the algorithm proposes the new light positions between these two light positions in a Gaussian distribution. The user can decide the number of new light positions. The standard deviation of the Gaussian distribution should be proportional to the gradient. We propose a parameter α that can be adjusted to get the best result. It is mentioned in equation 1. The user can also use a fixed standard deviation for this algorithm.

$$\sigma_{NewLp} = \alpha \nabla_{max} \tag{1}$$

where:
σ_{NewLp} = Standard deviation for distribution of new light positions,
α = Tunable parameter,
∇ = Absolute maximum gradient of POI.

This method targets the missing information from a sharp increase in pixel intensities using gradients. We compute the gradient using the finite differences method. It then places the new light positions in that region to capture the missing information. The gradient serves as an objective function that the algorithm tries to minimize. The stopping criteria for the algorithm is the threshold of the gradient. If after certain iterations, the maximum gradient of the signal reduces under a certain threshold, the algorithm will stop. The threshold depends on the tolerance parameter and standard deviation in the signal. It is defined as β in the equation 2

$$\beta = \gamma \times \sigma_{POI} \tag{2}$$

where:
β = Stopping criteria parameter,
γ = Tunable tolerance parameter,
σ_{POI} = Standard deviation of POI.

4. Experiments and results

We implemented our proposed methodology on the dataset delineated in section 4.1. Our investigation focused on two distinct regions of interest to authenticate the validity of the algorithm across diverse surfaces. In the first experiment, the region of interest has a linear and gradual response. We compare the result of the linear region with the homogenous equally spaced acquisition. The number of light positions for homogenous equally spaced and our algorithm was kept constant. In the second experiment, the region of interest has an anomaly and irregular response. We compare our results with a significantly dense acquisition for this experiment. These experiments validate that our algorithm adapts to diverse reflectance profiles on a surface.

4.1. Dataset

We performed the experiment on a coin named 'Coin of Emperor Nicolas' from the year 1897 as shown in figure 6. The coin 3D model was obtained from Sketchfab under a creative commons license [33]. We used Blender to capture the RTI setup images using the RTI plugin in Blender. The ground truth dataset was also created using a dense acquisition of 100 light positions at an elevation of 30 degrees. All the experiments were also performed at the same elevation of 30 degrees.

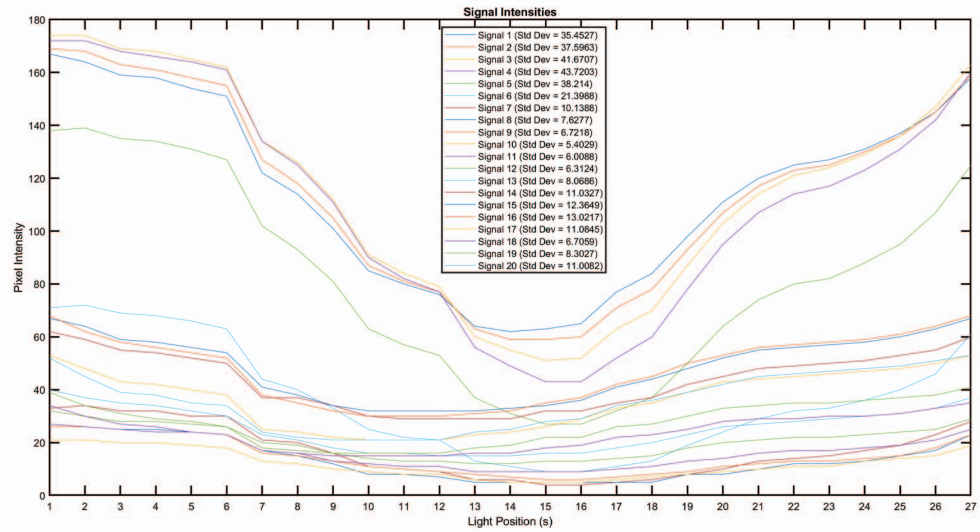


Figure 5: The figure shows 20 signals captured from the region of the eye of the coin. The x-axis shows different light positions along the ring. The standard variation of each signal is shown. It can be observed that there are 2 clusters of signals pointing towards two reflectance profiles in the eye region. One cluster of points is less sensitive to light positions and another cluster is varying highly with light positions. We deduce that the signal with the highest standard deviation is the Pixel of Interest (POI) and has information in the region that is to be revealed.

Figure 6: Coin of Emperor Nicolas from the year 1897 AD.

The method also has the ability to adapt itself according to the information coming from the new acquisitions. During each iteration, it calculates the standard deviation and finds the POI as explained in figure 5. This POI can or cannot be the same one during the acquisition. This makes our method adaptive to the whole ROI. The objective function is to minimize the gradient of the signal so that the maximum amount of information can be captured.

4.2. Experiment and results

We performed experiments to study the behavior of the algorithm. The fundamental goal of the algorithm is to identify abrupt, significant changes within a particular region, subsequently suggesting light positions in between these changes.

The first experiment explains our algorithm result on a linear reflectance region. Our algorithm tries to adapt itself and creates a result very similar to homogenous as explained in section 4.3. Figure 8 demonstrates the first experiment of the mouth region in the coin. The parameters used for this experiment are standard deviation ($Std_{lp} = 0.2$), number of new light positions ($n = 3$) stopping criteria ($gamma = 0.7$).

In the second experiment of the ear region, there is an anomaly that might be a result of a rendering error. Our algorithm is able to identify it and tries to explore it. Our algorithm was able to locate the anomaly and started to place light positions around it to capture information. This deduces that our algorithm can detect specularities. It can be observed in figure 9 that our algorithm has well-placed light positions around the anomaly. The dense acquisition of 100 light positions which we consider as ground truth here addresses anomaly with only 1 light position whereas our algorithm addresses anomaly with around 5 light positions. This is the idea of optimized acquisition. We want more dense acquisition around pixels where there is a strong non-linear response and sparse acquisition around pixels where there is a linear predictable response.

4.3. Comparison with homogenous equally spaced method

We compared the features of our acquisition method with the homogenous acquisition method. Figure 7 demonstrates the result for the mouth region of the surface. It is observed that the region of interest has a linear reflectance profile. Consequently, the algorithm did not necessitate any dense acquisition, with the acquisition demonstrating a bias towards homogeneity. However, the resulting normal map generated by our algorithm closely approximated the ground truth corroborating the effectiveness of our methodology. Moreover, comparing our result to the homogenous acquisition approach also yielded results near to ground truth. This underscores the robustness of our approach in achieving results of comparable quality, while potentially offering benefits in scenarios requiring adaptive acquisition strategies.

5. Conclusion

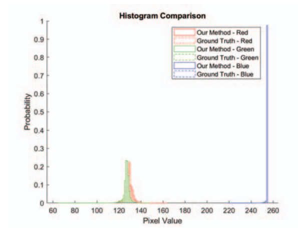
RTI acquisition is a tedious and painstaking task. Existing methods are either computationally very expensive or not practical thereby limiting its wide-scale adoption. Such limitations are underscored by the continued reliance on homogenous equally spaced acquisition approaches in museums and industry. The enduring popularity of the homogenous approach testifies to the existing gap in optimized, efficient, and user-friendly RTI acquisition methods.

We have investigated the problem of optimized acquisition for RTI in 2D ring setup in this paper. We have proposed a methodology based on signal analysis which is computationally very cheap. The average computational time for proposing new light positions is 0.48 seconds on MATLAB using 11 Gen Intel Core i7 cpu. This marks a notable reduction in comparison to existing algorithms, signaling a promising avenue for further exploration. Our algorithm can effectively address surfaces with both linear and significantly non-linear reflectance profiles.

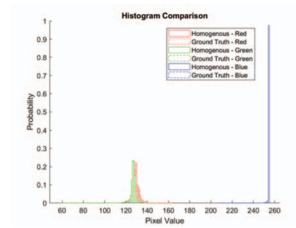
The optimization of acquisition represents a highly nuanced and complex domain. It necessitates the recognition of diverse perspectives, including those of experts in the field of cultural heritage. Our approach encourages a dynamic interplay between automated analysis and heritage expert knowledge. This is an effort to facilitate a more comprehensive and fine-tuned approach to acquisition optimization, maximizing the unique benefits derived from both technological advancement and human expertise. This study contributes a valuable proposition to the ongoing dialogue concerning the optimization of RTI acquisition, a realm that remains open for further investigation and development.

(a) Normal map created from our method's acquisition.

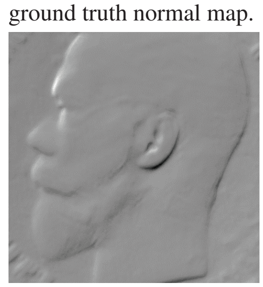
(b) Normal map created using homogenous equally spaced acquisition.



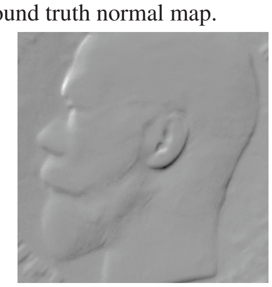
(c) Histogram comparison of our acquisition normal map with ground truth normal map. It can be seen that the histogram is overlapping the ground truth normal map.



(d) Histogram comparison of our acquisition normal map with ground truth normal map. It can be seen that the histogram is overlapping the ground truth normal map.

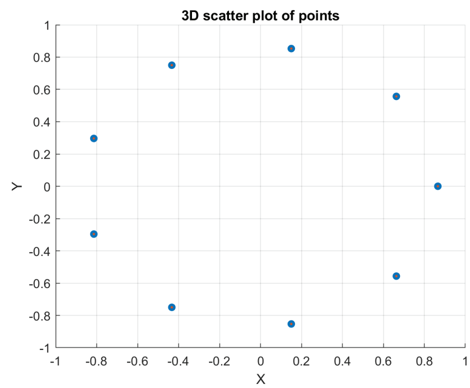


(e) Directional slope obtained using our acquisition

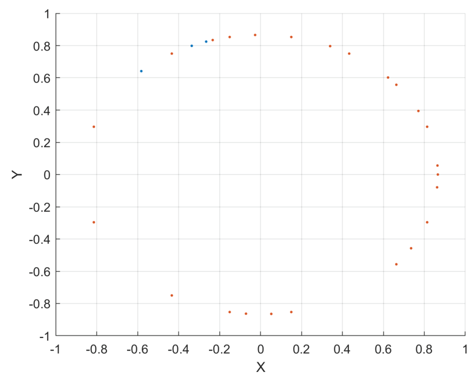


(f) Directional slope obtained using homogenous acquisition

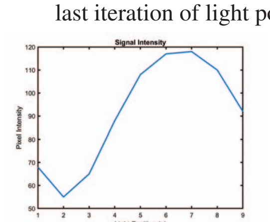
Figure 7: This figure shows features extracted from 27 homogenous light positions and 27 light positions from our algorithm as explained in the first experiment of the mouth region. The linear reflectance profile does not necessitate a dense acquisition and our algorithm performs as well as the homogenous method.



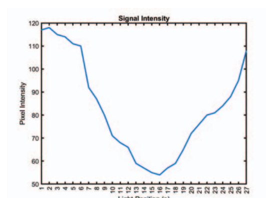
(a) 1^{st} iteration light positions.



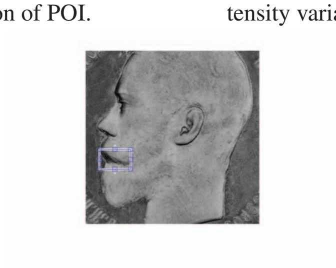
(b) 7^{th} iteration light positions. The blue dots are the last iteration of light positions.



(c) 1^{st} iteration: Signal intensity variation of POI.

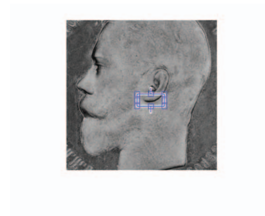


(d) 7^{th} iteration: Signal intensity variation of POI.

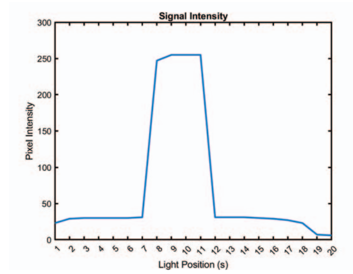


(e) The blue box shows the ROI to be optimized.

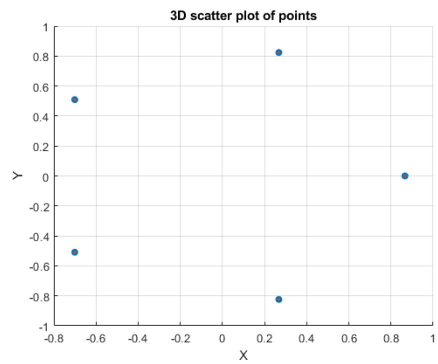
Figure 8: The figure demonstrates the experiment where a) Sparse acquisition for the initialization of algorithm, b) Light positions on final iteration, c) POI on acquisitions from 1^{st} iteration, d) POI on acquisitions from 7^{th} iteration, e) Surface under study.



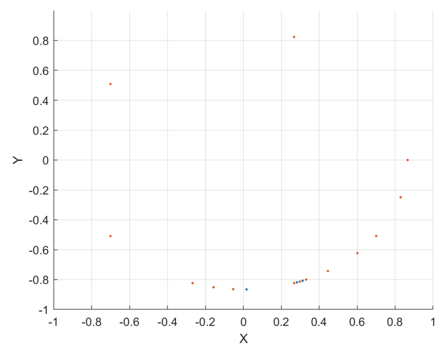
(a) The blue box shows the ROI to be optimized.



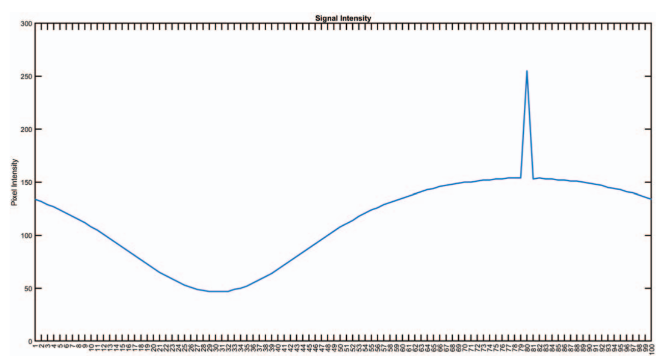
(b) POI after 6^{th} iteration.



(c) Initial light positions.



(d) 6^{th} iteration light positions. The blue dots are the last iteration of light positions.



(e) POI of ground truth (100 light positions)

Figure 9: The figure demonstrates that our algorithm is able to detect and explore anomaly in the subject. Our algorithm focuses on anomaly and suggests very dense acquisition for light positions sensitive to anomaly.

We plan to continue testing and refining our algorithm with the goal to enhance its practicality and user-friendliness. A key component of this procedure is to create an interactive and intuitive graphical user interface designed specifically for cultural heritage professionals. The ultimate aim will be to visualize latent features of signals and export optimized light position files to be used for acquisition. We also plan to scale and broaden our approach to 3D hemisphere.

References

[1] Flexible Solutions for Reflectance Transformation Imaging (RTI) — repository.si.edu. https://repository.si.edu/handle/10088/87619. [Accessed 21-08-2023]. 3

[2] Ahmed Abdrabou, Medhat Abdallah, Islam A Shaheen, and Hussein M Kamal. The application of multispectral imaging and Reflectance Transformation Imaging to an ancient Egyptian polychrome wooden stela. In *The 18th Triennial Conference of ICOM-CC, Copenhagen, Denmark*, pages 4–8, 2017. 2

[3] Vasileios Argyriou, Stefanos Zafeiriou, Barbara Villarini, and Maria Petrou. A sparse representation method for determining the optimal illumination directions in Photometric Stereo. *Signal Processing*, 93(11):3027–3038, 2013. 3

[4] Simon Brenner, Sebastian Zambanini, and Robert Sablatnig. An investigation of optimal light source setups for Photometric Stereo reconstruction of historical coins. In *GCH*, pages 203–206, 2018. 3

[5] Irina-Mihaela Ciortan, Andrea Giachetti, Sony George, and Jon Yngve Hardeberg. Fluorescence Transformation Imaging. In *Optics for Arts, Architecture, and Archaeology VIII*, volume 11784, pages 156–172. SPIE, 2021. 2

[6] Cl Connolly. The determination of next best views. In *Proceedings. 1985 IEEE international conference on robotics and automation*, volume 2, pages 432–435. IEEE, 1985. 3

[7] Andreas Doumanoglou, Rigas Kouskouridas, Sotiris Malassiotis, and Tae-Kyun Kim. Recovering 6d object pose and predicting next-best-view in the crowd. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3583–3592, 2016. 3

[8] Ondrej Drbohlav and Mike Chantler. On optimal light configurations in Photometric Stereo. In *Tenth IEEE International Conference on Computer Vision (ICCV'05) Volume 1*, volume 2, pages 1707–1712. IEEE, 2005. 3

[9] Tinsae G Dulecha, Filippo A Fanni, Federico Ponchio, Fabio Pellacini, and Andrea Giachetti. Neural Reflectance Transformation Imaging. *The Visual Computer*, 36:2161–2174, 2020. 2

[10] Silvia Florindi, Anna Revedin, Biancamaria Aranguren, and Vincenzo Palleschi. Application of Reflectance Transformation Imaging to experimental archaeology studies. *Heritage*, 3(4):1279–1286, 2020. 2

[11] Emily Frank, Sebastian Heath, and Chantal Stein. Integration of Photogrammetry, Reflectance Transformation Imaging (RTI), and Multiband Imaging (MBI) for Visualization, Documentation, and Analysis of archaeological and related materials. *ISAW Papers*, 2021. 2

[12] Hamza Gardi, Sebastian F Walter, and Christoph S Garbe. An optimal experimental design approach for light configurations in Photometric Stereo. *arXiv preprint arXiv:2204.05218*, 2022. 3

[13] Pascal Gautron, Jaroslav Křivánek, Sumanta N Pattanaik, and Kadi Bouatouch. A novel hemispherical basis for accurate and efficient rendering. *Rendering Techniques*, 2004:321–330, 2004. 2

[14] Andrea Giachetti, Irina Mihaela Ciortan, Claudia Daffara, Ruggero Pintus, and Enrico Gobbetti. Multispectral RTI Analysis of Heterogeneous Artworks. In Tobias Schreck, Tim Weyrich, Robert Sablatnig, and Benjamin Stular, editors, *Eurographics Workshop on Graphics and Cultural Heritage*. The Eurographics Association, 2017. 2

[15] Małgorzata Grzelec and Tomasz Łojewski. Applications of Reflectance Transformation Imaging (RTI) for Books and Objects on Paper. *Journal of Paper Conservation*, 24(1):16–30, 2023. 2

[16] Molly Hughes-Hallett, Christina Young, and Paul Messier. A review of RTI and an investigation into the applicability of micro-RTI as a tool for the documentation and conservation of modern and contemporary paintings. *Journal of the American Institute for Conservation*, 60(1):18–31, 2021. 2

[17] Ted Kinsman. An easy to build Reflectance Transformation Imaging (RTI) system. *The Journal of Biocommunication*, 40(1), 2016. 2

[18] Vlado Kitanovski and Jon Yngve Hardeberg. Objective evaluation of relighting models on translucent materials from multispectral RTI images. *IST International Symposium on Electronic Imaging Science and Technology*, 2021. 2

[19] Eleni Kotoula et al. Reflectance Transformation Imaging beyond the visible: ultraviolet reflected and ultraviolet induced visible fluorescence. In *Proceedings of the 43rd Annual Conference on Computer Applications and Quantitative Methods in Archaeology, Oxford*, pages 909–919, 2015. 2

[20] Eleni Kotoula and Maria Kyranoudi. Study of ancient Greek and Roman coins using Reflectance Transformation Imaging. *E-conservation magazine*, 25:74–88, 2013. 2

[21] David Lewis, Marvin Nurit, Hermine Chatoux, Fabrice Meriaudeau, and Alamin Mansouri. An automated adaptive focus pipeline for Reflectance Transformation Imaging. *Electronic Imaging*, 2021(18):63–1, 2021. 2

[22] Ramamoorthy Luxman, Yuly Emilia Castro, Hermine Chatoux, Marvin Nurit, Amalia Siatou, Gaëtan Le Goïc, Laura Brambilla, Christian Degrigny, Franck Marzani, and Alamin Mansouri. LightBot: A Multi-Light Position Robotic Acquisition System for Adaptive Capturing of Cultural Heritage Surfaces. *Journal of Imaging*, 8(5):134, 2022. 2

[23] Ramamoorthy Luxman, Marvin Nurit, Gaëtan Le Goïc, Franck Marzani, and Alamin Mansouri. Next Best Light Position: A self configuring approach for the Reflectance Transformation Imaging acquisition process. *Electronic Imaging*, 2021(5):132–1, 2021. 3

[24] Lindsay William Macdonald. *Realistic visualisation of cultural heritage objects*. PhD thesis, UCL (University College London), 2015. 2

[25] Tom Malzbender, Dan Gelb, and Hans Wolters. Polynomial texture maps. In *Proceedings of the 28th annual conference on Computer graphics and interactive techniques*, pages 519–528, 2001. 2

[26] Marcello Manfredi, Greg Bearman, Greg Williamson, Dale Kronkright, Eric Doehne, Megan Jacobs, and Emilio Marengo. A new quantitative method for the non-invasive documentation of morphological damage in paintings using RTI surface normals. *Sensors*, 14(7):12271–12284, 2014. 2

[27] Marcello Manfredi, Greg Williamson, Dale Kronkright, Eric Doehne, Megan Jacobs, Emilio Marengo, and Gregory Bearman. Measuring changes in cultural heritage objects with Reflectance Transformation Imaging. In *2013 Digital Heritage International Congress (DigitalHeritage)*, volume 1, pages 189–192. IEEE, 2013. 2

[28] Harold Mytum and JR Peterson. The application of Reflectance Transformation Imaging (RTI) in historical archaeology. *Historical Archaeology*, 52:489–503, 2018. 2

[29] Marvin Nurit, Y Castro, Abir Zendagui, Gaëtan Le Goïc, Hugues Favreliere, and Alamin Mansouri. High dynamic range Reflectance Transformation Imaging: an adaptive multi-light approach for visual surface quality assessment. In *Fourteenth International Conference on Quality Control by Artificial Vision*, volume 11172, pages 276–284. SPIE, 2019. 2

[30] Anthony Pamart, Federico Ponchio, Violette Abergel, A Alaoui M'Darhri, Massimiliano Corsini, Matteo Dellepiane, François Morlet, Roberto Scopigno, and Livio De Luca. A complete framework operating spatially-oriented RTI in a 3d/2d cultural heritage documentation and analysis tool. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 42:573–580, 2019. 2

[31] Daryl Peralta, Joel Casimiro, Aldrin Michael Nilles, Justine Aletta Aguilar, Rowel Atienza, and Rhandley Cajote. Next-best view policy for 3d reconstruction. In *Computer Vision–ECCV 2020 Workshops: Glasgow, UK, August 23–28, 2020, Proceedings, Part IV 16*, pages 558–573. Springer, 2020. 3

[32] Gilles Pitard, Gaëtan Le Goïc, Alamin Mansouri, Hugues Favrelière, Simon-Frederic Desage, Serge Samper, and Maurice Pillet. Discrete modal decomposition: a new approach for the reflectance modeling and rendering of real surfaces. *Machine Vision and Applications*, 28:607–621, 2017. 2

[33] Luke Reid, Seaneen McDougall, and Caroline Erolin. Sketchfab: An educational asset for learning anatomy. *Journal of Anatomy*, 236(S1):267, 2020. 4

[34] Sunita Saha, Amalia Siatou, Alamin Mansouri, and Robert Sitnik. Supervised segmentation of RTI appearance attributes for change detection on cultural heritage surfaces. *Heritage Science*, 10(1):1–15, 2022. 2

[35] Jacqueline F DiBiasie Sammons. Application of Reflectance Transformation Imaging (RTI) to the study of ancient graffiti from herculaneum, italy. *Journal of Archaeological Science: Reports*, 17:184–194, 2018. 2

[36] William R Scott, Gerhard Roth, and Jean-François Rivest. View planning for automated three-dimensional object reconstruction and inspection. *ACM Computing Surveys (CSUR)*, 35(1):64–96, 2003. 3

[37] Amalia Siatou, Yuly Castro, Marvin Nurit, Hermine Chatoux, Gaetan Le Goïc, Christian Degrigny, Laura Brambilla, and Alamin Mansouri. A methodological approach for Multi-Temporal Tracking of Silver Tarnishing. In *Proceedings of the 4th ACM International workshop on Structuring and Understanding of Multimedia heritAge Contents*, pages 5–13, 2022. 2

[38] Amalia Siatou, Marvin Nurit, Yuly Castro, Gaëtan Le Goïc, Laura Brambilla, Christian Degrigny, and Alamin Mansouri. New methodological approaches in Reflectance Transformation Imaging applications for conservation documentation of cultural heritage metal objects. *Journal of Cultural Heritage*, 58:274–283, 2022. 2

[39] Amalia Siatou, Marvin Nurit, Gaëtan Le Goïc, Alamin Mansouri, Laura Brambilla, and Christian Degrigny. Reflectance Transformation Imaging feature maps for visual documentation of metals objects. In *Metal 2022, proceedings of the interim meeting of the ICOM-CC metals working group*. ICOM-CC; The National Museum of Finland, 2022. 2

[40] Stephen H Westin, James R Arvo, and Kenneth E Torrance. Predicting reflectance functions from complex surfaces. In *Proceedings of the 19th annual conference on Computer graphics and interactive techniques*, pages 255–264, 1992. 2

[41] Robert J Woodham. Photometric method for determining surface orientation from multiple images. *Optical engineering*, 19(1):139–144, 1980. 1

[42] Abir Zendagui, Gaëtan Le Goïc, Hermine Chatoux, Jean-Baptiste Thomas, Yuly Castro, Marvin Nurit, and Alamin Mansouri. Quality assessment of dynamic virtual relighting from RTI data: application to the inspection of engineering surfaces. In *Fifteenth International Conference on Quality Control by Artificial Vision*, volume 11794, pages 94–102. SPIE, 2021. 2