

# Hyperspectral, Multispectral, and Multimodal (HMM) Imaging: Acquisition, Algorithms, and Applications

Edited by

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## Abstract

In the last couple of decades, hyperspectral, multispectral, and multimodal (HMM) imaging has emerged as an essential tool in various fields of science, medicine, and technology. Compared to integrated broad-band information as, e.g., present in RGB images, HMM imaging strives to acquire a multitude of specific narrow bands of the electromagnetic spectrum in order to solve specific detection or analysis tasks. HMM research is interested in studying light-matter interaction in a wide range of wavelengths from the high energy radiation down to Terahertz radiation (sub-millimeter waves). Furthermore, combining spectral data captured using different imaging modalities can unveil additional information of the scene that is not revealed solely by each of the individual imaging modalities.

The workshop intended to connect researchers from different disciplines that involve HMM imaging and analysis. Even though there are very different approaches towards HMM imaging research and application, the main hypothesis of the workshop was that there is a large amount of common goals, approaches and challenges. Thus, these disciplines will benefit from intensifying communication and knowledge transfer and an out-of-the-box thinking and a broader vision of the fundamental concepts regarding common fields of interest, e.g., in the configuration of HMM acquisition systems, data analysis, and improved development techniques by common software bases and validation tools.

The seminar succeeded in bringing together researchers from different scientific communities and fostering open-minded discussions across very different fields of research and application.

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## 1 Executive Summary

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On the last day of the seminar, the attendees had a very intense discussion about the usefulness of the seminar itself, the grand challenges related to the highly interdisciplinary field of research, and the next steps that should be taken in order to further improve on the cross-fertilizing effects in hyperspectral, multispectral, and multimodal imaging.

### Take Home Messages

All attendees agreed on the high quality and open mindedness of the discussions at both, the group level, e.g., in the plenary sessions and the working groups, and also on personal level. All participants assess this Dagstuhl seminar as a great success, especially due to the interdisciplinary discussion and the new insights resulting from this. Despite differences of the individual fields present in the seminar, e.g., remote sensing, color reproduction, and material classification, and despite the wide variety of applications such as medical, environmental monitoring, and arts, a large set of common questions and problems could be identified. All attendees highly appreciated the fact, that unlike in conferences, which usually have a rather narrow perspective on HMM challenges and solutions, as they usually address a single community with a very similar perspective on the field, this seminar brought together people with very different points of view.

This Dagstuhl seminar was a starting point of a number of connections that could be established directly, and several mid-, and maybe even long-term collaborations and joint research actions. There have been several highlights related to the full pipeline from data acquisition, via data processing to applications.

### Grand Challenges

On the basis of common and interdisciplinary ground setup in this seminar, several challenges have been identified, which the seminar's attendees see as important to be addressed in further research and engineering work.

**Data Acquisition** Independent of the specific range of the addressed electromagnetic spectrum, the seminar participants see a severe restriction in the usage of HMM sensors due to their inflexibility, e.g., in selecting spectral bands, bulkiness, high calibration efforts, and acquisition speed (see also the working group report on this topic). Enhancing on these limiting factors has the potential to bring about fundamentally new spins in various application domains. Some approaches presented at the workshop have the potential to push back these limits to some degree. On the other hand, most likely there will be no general purpose HMM acquisition device available in the next decades that covers the majority of application requirements. Still, the seminar attendees agree on

the importance of enhancing the applicability of existing and future acquisition devices towards more flexible band selection, fast and efficient, (semi-)automated calibration, and, for some applications, compactness. Ideally, future research provides means for an abstract definition of application specific characteristics from which a specific selection and/ or instantiation of an acquisition device can be deduced.

**Data Processing and Validation** Regarding data processing and validation, three main topics have been discussed: The usefulness and limitations of machine learning and, especially, deep learning (see working group report), the importance of verified and metric data, and the need for a proper reference and benchmarking data set. Even though there are and have been ongoing activities in spectral normalization and validation, e.g., on the level of CIE or other standardization institutions, or in the field of metrology, there still is the lack of widely existing and accepted methods and data even if restricted to specific fields of application.

The seminar participants see a huge potential in all three areas. Still, major obstacles have to be overcome in order to leverage these potentials. In machine learning/ deep learning, one main issue is the lack of guarantees that the results obey specific constraints to, e.g., physical limits or relations. The lack of verified, metric data, and proper reference and benchmarking data, on the other hand, can only be overcome if there is a stronger common basis for best practice within and, even more important, between the HMM sub-disciplines.

**Information Exchange** The existence of common information bases is tightly linked to the prior point regarding data processing and validation. So far, there are only few options and pseudo-standard for sharing data and algorithms. While there are good examples, e.g., Open CV library in computer vision, setting up this kind of “standard” is, and will be, much harder in the diverse and partially fragmented HMM research domain. Apparently, this chicken-egg problem can only be solved from within the involved research domains themselves by the normative power of fact of the actions taken by the researchers themselves.

### Next Steps

Participants discussed various options for future activity as a follow-up on this Dagstuhl seminar. As one essential restriction of the discussion, attendees became aware of their own limitations in knowing all relevant work and requirements existing in the HMM research subfields. Therefore, the obvious approach to enhance the fields’ convergence by publications, e.g., a special issue or book, and/ or workshops has not the highest priority, even though an introductory workshop or piece of literature for 1st year PhD students would be highly appreciated.

However, participants of Dagstuhl seminar see two main options to proceed in order to keep the initiated process of convergence going and to improve on at least two of the three main challenges identified, i.e., regarding data processing and validation and the exchange of information.

**HMM Webpage:** As there is a severe lack in common information widely used and recognized, the group of researchers who attended Dagstuhl seminar see the potential of a common, web-based information platform.

In this respect, Masahiro Yamaguchi is open to provide the already established web-link multispectral.org and Andreas Kolb will investigate options for setting up and hosting this kind of platform. In any case, this kind of activity needs to rest on several shoulders, thus the attendees are called to follow through with the activities, on the operative level.

**Follow-up Dagstuhl Seminar:** As Dagstuhl supports follow-up seminars, the attendees agree on the usefulness of having this kind of seminar in order to evaluate the common, interdisciplinary activities that arose from the first Dagstuhl seminar. In case of a new edition of the workshop, participants agree on having more industrial partners involved.

## 2 Table of Contents

### Executive Summary

<i>Andreas Kolb, Gonzalo R. Arce, Richard Bamler, Shida Beigpour, Hilda Deborah, and Jon Yngve Hardeberg</i> . . . . .	15
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### Overview of Talks

Imaging Spectroscopy in Earth Observation – Sensors, Tasks, and Challenges <i>Richard Bamler</i> . . . . .	20
Hyperspectral Imaging for Image-based Rendering? <i>Shida Beigpour</i> . . . . .	20
Quantifying Composition of Human Tissues from Multispectral Images using a Physics-based Model of Image Formation <i>Ela Claridge</i> . . . . .	21
Is it Possible to Design Optimal Cameras for Robotic Vision? <i>Donald G. Dansereau</i> . . . . .	22
Quality Assessment of Spectral Image Processing Algorithms <i>Hilda Deborah</i> . . . . .	22
Trends, Issues, and Opportunities in Fusion-related Problems <i>Nicolas Dobigeon</i> . . . . .	23
Trends, Issues, and Opportunities in Unmixing-related Problems <i>Nicolas Dobigeon</i> . . . . .	24
HMM Imaging of the Aquatic Ecosystem <i>Peter Gege</i> . . . . .	25
Assessing the Need for Fundamental Biophysical Data <i>Gladimir V. G. Baranoski</i> . . . . .	25
Spectral to the People: Towards Affordable and Easy-to-use Spectral Imaging <i>Jon Y. Hardeberg</i> . . . . .	26
Visualization and Visual Analysis of Hyperspectral, Multispectral, and Multimodal Data <i>Andreas Kolb</i> . . . . .	26
Hyperspectral Data for Terrain Classification <i>Dietrich Paulus</i> . . . . .	27
Classification of Multimodal Data in Raman- and IR Microspectroscopy <i>Christoph Pomrehn</i> . . . . .	28
Metrological Hyperspectral Image Analysis and Processing <i>Noël Richard</i> . . . . .	28
Visual Analysis of Fine Details in Raman Microscopy <i>Christoph Markus Schikora</i> . . . . .	29
Spectral Filter Array Cameras <i>Jean-Baptiste Thomas</i> . . . . .	30
Spectral Imaging for Fluorescent Objects <i>Shoji Tominaga</i> . . . . .	31

Exploiting Human Eyes for Remote Sensing <i>Devis Tuia</i> . . . . .	31
Squeezing Spectra: Hot Topics at the Color Imaging Lab of the University of Granada <i>Eva M. Valero Benito</i> . . . . .	32
Optical Imaging Techniques for Non-contact Measurements of Vital Functions and Diagnosis of Tissues in Medicine <i>Rudolf Verdaasdonk, John Klaessens, and Herke Jan Noordmans</i> . . . . .	32
Introduction to THz Imaging and Spectroscopy <i>Anna Katharina Wigger</i> . . . . .	33
Toward Practical Applications of High-Resolution Multispectral/ Hyperspectral Video <i>Masahiro Yamaguchi</i> . . . . .	33
Deep Learning in Remote Sensing <i>Xiaoxiang Zhu</i> . . . . .	34
<b>Working groups</b>	
Hyperspectral, Multispectral and Multimodal Image Acquisition <i>Donald G. Dansereau</i> . . . . .	35
Deep Learning for Analysis of Multispectral Data <i>Dietrich Paulus and Richard Bamler</i> . . . . .	37
User Involvement, Validation Tools, Data, and Software Sharing <i>Rudolf Verdaasdonk</i> . . . . .	39
<b>Participants</b> . . . . .	42

### 3 Overview of Talks

#### 3.1 Imaging Spectroscopy in Earth Observation – Sensors, Tasks, and Challenges

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Imaging spectroscopy in Earth observation is used from satellites, airplanes or drones to map land cover/ land use, materials, water quality, soil properties, hazards and risks, etc. Data processing results in maps of either detection or classification or of continuous-valued variables like plant water content or chlorophyll concentration. Particularly stringent requirements are posed from remote sensing of inland waters.

DLR is responsible for two spaceborne hyperspectral instruments and missions, DESIS (launch 2018 onboard the ISS) and the satellite EnMAP (launch 2020). While DESIS operates in the VNIR domain, EnMAP features about 200 channels in both VNIR and SWIR.

Spaceborne multi-/ hyperspectral instruments suffer from the spatial/spectral resolution trade-off. Therefore, data fusion for sharpening is often required. This is only one challenge of hyperspectral data processing among many others, like atmospheric correction, spectral unmixing, possible low SNR, spectral variability, clouds and the lack of sufficient ground truth data for training and validation.

Finally the question is raised how deep learning can solve some of these challenges. This question has been discussed in a subsequent workshop.

#### 3.2 Hyperspectral Imaging for Image-based Rendering?

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Joint work of Beigpour, Shida; Shekhar, Sumit; Myszkowski, Karol; Seidel, Hans-Peter

Photographs and videos are 2D projections of the three-dimensional scene that encode the characteristics of that scene. While such medium is not able to preserve all the aspects of the scene, it still contains valuable information which enables e.g., human subjects to understand the scene. Human perception plays an important role in this context. It has been shown that human perception relies on certain heuristics rather than performing inverse optics.

Image-based inverse rendering techniques use such cues to infer a mid-level representation of the scene known as “intrinsic layers” (i.e., reflectance, shading, and specularity) in order to then be able to modify certain aspects such as materials, illumination, and texture of the objects in the scene. Each intrinsic layer encapsulates certain characteristics of the image allowing for more control over the quality of the results. For example, as specular layer encapsulates the surface gloss, metallic appearance can be rendered by filtering this layer.



We introduce complex perceptual appearance effect (e.g., translucent, gold-plated, weathered, etc.) achieved by signal-based filtering of intrinsic layers. This enables users to interact with the scene in Virtual Reality (VR) and Augmented Reality (AR) applications. So far, spectral imaging has hardly been considered for this task. We show the importance of such data in correctness of our methods as well as datasets and benchmarks.

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### 3.3 Quantifying Composition of Human Tissues from Multispectral Images using a Physics-based Model of Image Formation

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**Joint work of** Cotton, Symon; Preece, Steven; Styles, Iain

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**URL** <http://dx.doi.org/10.1016/j.media.2006.05.007>

Through an understanding of the image formation process, diagnostically important facts about the internal structure and composition of tissues can be derived from their multispectral images. A physics-based model provides a cross-reference between image values and the underlying histological parameters. It is constructed by computing the spectral composition of light remitted from the tissue given parameters specifying its structure and optical properties. Once the model is constructed, for each pixel in a multispectral image its histological parameters can be computed by model inversion. Represented as images, these 'parametric maps' show the concentration of relevant absorbers and volumetric density of scattering structural tissue components. Skin parameters can be recovered with accuracy sufficient for diagnostic use. Retinal imaging poses many challenges, including limited incident illumination, eye movement during multispectral image acquisition, lack of spatial

calibration of illumination, lack of flexible tuneable multispectral filters, mathematically and computationally complex inversion and difficulties with validation against histology.

### 3.4 Is it Possible to Design Optimal Cameras for Robotic Vision?

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**Joint work of** Donald G. Dansereau, Daniel Bongiorno, Tom Bridge, Mitch Bryson, Oscar Pizarro, Stefan B. Williams

I give two examples of hyper/multi-spectral imaging in robotics: shark detection from flying robots, and seabed classification from underwater robots. I demonstrate that as few as four colour bands are required to offer increased performance in aerial imaging through water, and even single-pixel spectrometers can improve classification results in autonomous underwater vehicle (AUV)-based seabed survey.

I use these examples to introduce an unresolved problem in robotic vision: How does one design the optimal camera for a given task? Approaches from the robotics and computational imaging communities generally maximize colour fidelity rather than system-level performance, or rely on large training sets and lack generality. Meanwhile, information theory addresses optimal sensing in simple scenarios, but does not fully address the statistics of visual sensing as shown by the dramatic results recently demonstrated in deep learning, which leverages complex learned visual priors.

I raise the question of how one might go about designing optimal cameras for robotic vision, with the hope of uncovering relevant tools and principles from within the HMM community.

### 3.5 Quality Assessment of Spectral Image Processing Algorithms

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**Joint work of** Noël Richard, Jon Yngve Hardeberg, Christine Fernandez-Maloigne  
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In the past decades, hyperspectral imaging has been increasingly exploited as it offers a significant gain of accuracy. However, accurate measurements do not entail accurate final processing results. Accuracy can only be obtained when bias, uncertainty, etc., are managed at each level of the processing. Hence the need to enforce metrology to spectral image processing. In my talk, I showed several quality assessment protocols that were designed to metrologically validate spectral difference functions, spectral ordering relations, and morphological crack detection algorithm. Nevertheless, the design of the protocol is generic and can be adapted to other spectral processing algorithms.

### 3.6 Trends, Issues, and Opportunities in Fusion-related Problems

*Nicolas Dobigeon (University of Toulouse, FR)*

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This talk discusses some open issues related to the problem of fusing multiple images of different spatial and spectral resolutions.

First, it discusses the inverse problem framework, generally considered to conduct this task. In particular, the choice of the regularization is still a challenging question and can be motivated from different points of view: to ease the computations, to promote spatial or spectral features of the fused image, to ensure physically motivated modeling, to exploit outputs from machine learning techniques. Besides, the question of the need for regularization is also discussed since, from a Bayesian perspective, the maximum a posteriori estimation always leads to a trade-off that might lead to unacceptable solution.

Most of the fusion techniques rely on the prior availability of registered, corrected pairs of images to be fused, and possibly on the technical specification of the sensors. In practice, this availability can be limited.

Some opportunities are also discussed. The traditional use case for fusion consists in fusing a pair of optical images of different spatial and/or spectral resolutions acquired at the same date. However, over applicative scenario of interest can appear. For instance, is there any interest to deal with a pair of images without complementarity in terms of spatial and spectral information? How can we fuse more than two images? Moreover, when the images have been acquired at different time instants, detecting changes between these images can be envisioned as a change detection problem. Another open question is to process non-optical data (e.g., SAR images, LiDAR, database). Finally, the main interest of the fused product is questioned, besides visualization perspectives. For a particular task (e.g., classification, detection, unmixing), is there any interest to fuse before this task? Should we design task-driven fusing schemes?

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### 3.7 Trends, Issues, and Opportunities in Unmixing-related Problems

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This 5-minute talk provides some insights to unmixing-related problems, even in the conventional linear mixing framework.

First, it discusses the choice of the mixing models to be used when conducting unmixing. There are plenty of nonlinear and robust models. An open question is: How and when should we choose a particular model? A tentative response has been brought for vegetated areas. Moreover, overcoming the inherent spectral variability is also a challenging question. To validate these models and the associated unmixing algorithms, no standard benchmark has been proposed. Moreover, this validation requires the availability of ground-truth data, which is not common.

Then this talk discusses non-standard algorithmic schemes and implementations. Such strategies are generally necessary to face with huge data volume. Multi-temporal image unmixing and hyperspectral video unmixing are promising research issues, which can be tackled off-line, on-line or in a distributed manner.

The question of the supervision of unmixing procedures is also discussed. Most of the research works tend to propose fully unsupervised unmixing procedure. However is it really beneficial? Indeed, in most applicative contexts, some external information is available and can be incorporated.

Finally, one wonders if there is any real interest to unmix, from an end-users point-of-view. For instance, for the mapping of a particular single material, could we design some partial unmixing techniques?

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### 3.8 HMM Imaging of the Aquatic Ecosystem

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**Main reference** P. Gege (2017): Radiative transfer theory for inland waters. In: Mishra D.R., Ogashawara I., Gitelson A.A. (Eds.), *Bio-Optical Modelling and Remote Sensing of Inland Waters*. Elsevier, p. 27-69. ISBN: 978-0-12-804644-9

**URL** <http://dx.doi.org/10.1016/B978-0-12-804644-9.00002-1>

The oceans are monitored since decades using multispectral sensors on satellite, but very little information is available for the majority of inland waters since they are too small for ocean colour satellites, optically too complex for most multispectral sensors and too numerous (around 120 million lakes > 15 m) for traditional sampling. Since inland waters cover less than 4% of Earth's surface, their importance for global processes has long been overlooked, but new data indicate that they may be more important than the oceans in some aspects, e.g. they bury twice as much carbon from the atmosphere by sedimentation. A number of hyperspectral space sensors will be launched in the next years whose resolution of 30 m is suited to monitor water quality of nearly 90% of the lake areas. I present the principles of the models that are used to analyse hyperspectral data over water and discuss the potential and challenges of hyperspectral imaging for optically complex water types.

### 3.9 Assessing the Need for Fundamental Biophysical Data

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Predictive models of light and matter interactions are employed in a wide range of applications in several fields such as computer graphics, remote sensing and biomedical optics, just to name a few. It is a well-known fact that a well-designed model is of little use without reliable specimen characterization data (e.g., thickness and pigment concentrations) to be used as input, and reliable evaluation data (e.g., spectral reflectance and transmittance) to be used in the assessment of its predictive capabilities. Ideally, the specimen's characterization data to be incorporated into a model should correspond to the specimen used to obtain the measured data employed in its evaluation. However, the few spectral datasets available in the literature rarely provide a comprehensive description of the target specimens. Data is even more scarce for materials in their pure form, such as natural pigments, whose absorption profile is often obtained either through inversion procedures, which may be biased by the inaccuracies of the inverted model, or does not take into account in vivo and in vitro discrepancies. In this talk, we discuss these issues and their practical implications for the development of robust hyperspectral technologies relying on light interaction models.

### 3.10 Spectral to the People: Towards Affordable and Easy-to-use Spectral Imaging

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In recent decades there has been a significant volume of research carried out in the field of spectral imaging, that is, imaging systems and methodologies in which the spectral radiance or reflectance of the imaged scene or objects is captured and processed. Such systems have shown their usefulness in many application domains such as cultural heritage, medical imaging, biometrics, remote sensing, food quality, etc.

High spectral accuracy generally comes at a high cost, for instance using so-called push-broom line-scanning hyperspectral imaging technology. On the other hand, multispectral imaging systems with a lower number of spectral channels have been developed, in which typically multiple subsequent image capture operations with a 2D panchromatic image sensor is needed, together with optical filters mounted on a filter wheel or liquid crystal tunable filters. While such systems are generally cheaper, their cost is still prohibitive for many applications. Furthermore both approaches face obvious challenges when applied to real-world non-stationary scenes. And finally users often find the technologies to be lacking in user friendliness, for instance due to the need for complicated calibration procedures and limited software for analysing the data. In summary, key obstacles to broader acceptance of spectral imaging for new applications are cost, user friendliness, and speed.

Recently, new approaches for faster and more practical spectral image acquisition have been proposed, including the three promising ideas of using spectral filter arrays, using two color cameras with additional optical filters in a stereoscopic configuration, and using active LED illumination in conjunction with RGB or panchromatic area image sensors. In this presentation we gave a brief overview our recent research using these three approaches, discuss their advantages and disadvantages, as well as directions for further research aiming for faster, cheaper, and more user friendly solutions for spectral imaging.

### 3.11 Visualization and Visual Analysis of Hyperspectral, Multispectral, and Multimodal Data

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Compared to fully automated techniques for multi- and hyperspectral image analysis, interactive visual analysis approaches allow the ad hoc incorporation of expert knowledge, thus making the exploration of the unknown possible. This, furthermore, gives option to understand the retrieved results in their contexts. However, there are several challenges to any interactive visual analysis approach. In order to prevent the human involvement to be too time consuming, efficient and flexible to use analysis components are needed. Furthermore, the dimensionality of both, the visual feedback as well as the interaction mode is very limited, and the visual analysis results are often only qualitative.

In this presentation, two examples are given, incremental spectral unmixing and error guided endmember selection. Incremental spectral unmixing addresses the need of providing

interactive unmixing functionalities, which are able to give direct feedback to the user if he/she changes the set of endmembers and/or the unmixing conditions. These kind of approaches can predict the unmixing result as user changes the endmember set incrementally, i.e., by adding or removing a single endmember. Error guided endmember selection is a concept in which the user get more sophisticated feedback regarding the quality of unmixing. Common approaches use a pre-defined, scalar error metric, which solely given information about the fitting quality of the spectral reconstruction with respect to the given raw spectrum. The presented approach color-codes the spectral signature of the reconstruction error on a coarse level, thus supporting the identification of regions in the multispectral image that have similar spectral error characteristics.

Future visual analysis might incorporate prominent techniques used for automated classification and detection tasks, such as machine learning and more complex optimization methods.

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## 3.12 Hyperspectral Data for Terrain Classification

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**Joint work of** Christian Winkens

**Main reference** Christian Winkens, Volkmar Kobelt, Dietrich Paulus: Robust Features for Snapshot Hyperspectral Terrain-Classification. CAIP (1) 2017: 16-27

**URL** <http://dblp.org/rec/conf/caip/WinkensKP17>

**Main reference** Christian Winkens, Florian Sattler, Dietrich Paulus: Hyperspectral Terrain Classification for Ground Vehicles. VISIGRAPP (5: VISAPP) 2017: 417-424

Hyperspectral snapshot cameras in NIR and VIS can be used to navigate autonomous vehicles. We show how data acquired from these devices can be used to classify terrain into drivable and non-drivable areas. This is of particular importance for unstructured outdoor areas. One specific problem is to identify shadowed areas as they may lead to different features and as they are a source of possible misclassification. We show some approaches to detect shadows and to extend the terrain classification at this point. We provide a database of annotated videos from a multispectral stereo camera for evaluation of experiments.

### 3.13 Classification of Multimodal Data in Raman- and IR Microspectroscopy

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Joint work of Daniel Klein

The field of vibrational microspectroscopy can generally be subdivided into the concepts of Raman- and IR microspectroscopy. Both approaches aim to the identification and localization of specific molecular vibrations in matter and thus, to the identification of the substance. Due to the rule of mutual exclusion, basic molecular vibrations that can be detected by one of these modalities, can not be detected by the other and vice versa. Consequently, a multimodal approach might provide complementary information about the object under test. In this talk, we presented results of a classification study determined by comparing monomodal and multimodal classification rates and class error distributions of data, derived from a polymer sample. It turned out, that a clear majority of feature-classifier constellations show a numerical improvement in classification rates.

### 3.14 Metrological Hyperspectral Image Analysis and Processing

*Noël Richard (University of Poitiers, FR)*

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Joint work of Hilda Deborah and Audrey Ledoux

Are spectral acquired values measures or just data?

Considering an acquired value as a measure allows to take care about some associated properties, like accuracy, bias and uncertainty. Using it as a simple data induces to consider at the same level of information an inaccurate value and a value with a reduced uncertainty, with the associated consequences to the final decision. All the objectives of the metrological processing or analysis are to preserve the spectral and spatial accuracy of the acquired measures in the computation stages.

To preserve the metrological properties of the measures, adapted mathematical definitions of the spectral acquisitions must be adopted. Consequently, hyperspectral measures must be defined as functions over the wavelengths and not as vector or probability density functions (proof are in the proposed bibliography). Inside this definition, acquired spectra are defined as sampling of a physical/ optical continuous function (radiance, reflectance, irradiance). Consequently, adapted spectral distance/ difference functions must be defined and validated under metrological constraints. A first solution is provided (Kullback-Leibler pseudo-divergence or KLPD) respecting all the expected properties expected from a similarity or distance function. In addition, the KLPD naturally splits the spectral similarity as a sum of a shape and an energy difference. Thanks to this construction, analysis tools based on histograms of differences are defined, allowing to process statistical statistics and models of mixing (GMM).

In the context of multispectral images, the spectrum is considered as being expressed inside a non-orthogonal basis of functions (the spectral sensitivity curves of the channel sensor). Thanks to this definition, the metrological processing tools takes into consideration this inter-dependency using a scalar product of functions. In addition, the Di-Zenzo expression

allowing to define a gradient inside an orthogonal basis is extended to the non-orthogonal case using a Gram matrix producing so a generic expression for any case of multi-spectral images. Results are provided for colour and multispectral (Silios sensor, 8 spectral channels + 1 pan-chromatic channel).

We conclude about some challenges that need to be addressed collectively in the following months/ years.

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## 3.15 Visual Analysis of Fine Details in Raman Microscopy

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**Joint work of** Plack Markus, Bornemann Rainer, Haring Bolivar Peter, Kolb Andreas

**Main reference** Christoph M. Schikora, Markus Plack, Rainer Bornemann, Peter Haring Bolivar, Andreas Kolb, "Visual Analysis of Confocal Raman Spectroscopy Data using Cascaded Transfer Function Design", In *Computer Graphics Forum*, 36(3), 2017

**URL** <http://dx.doi.org/10.1111/cgf.13183>

Analysis of fine details like grain boundaries in mono-layer graphene is a directly impossible task in confocal Raman microscopy CRM with usual confocal Raman imaging. Current experiments show the possibility to overcome this limitation caused by the resolution limits, by the high amount of data and by to CRM adapted interactive exploitative visual analysis concepts, in which the usage of spatial features and oversampling or super resolution is the key. This opens not only new applications in quality control of graphene and other carbon polymers, but also generally an approach for imaging of fine details below optical limits in confocal Raman microscopy.

### 3.16 Spectral Filter Array Cameras

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Spectral Filter Arrays camera provides a snapshot imaging technology to acquire multispectral images. Advantage of this technology is that it can be embedded into a very standard imaging pipeline with minor modification. Recent advances and commercial availability rise the question on the uses and actual limitations of this technology. I define the imaging procedure and the pipeline, and illustrate identified issues.

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### 3.17 Spectral Imaging for Fluorescent Objects

*Shoji Tominaga (Chiba University, JP)*

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**Main reference** S. Tominaga, K. Hirai, and T. Horiuchi, Estimation of bispectral Donaldson matrices of fluorescent objects by using two illuminant projections, *Journal of the Optical Society of America A*, Vol. 32, No. 6, pp.1068-1078, 2015.

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**URL** <http://www.ntnu.edu/employees/shojit>

I gave a talk about Spectral Imaging for Fluorescent Objects. Use of fluorescent materials has increased in our daily lives. All sorts of objects we see in each day often include fluorescence. First, I presented the visual effects of fluorescence. In fact, because of fluorescent emission, many fluorescent surfaces appear brighter and more vivid than the original object color surface. Next, I described the principle of fluorescence. The fluorescent characteristics are well described in terms of the bispectral radiance factor, which can be summarized as a Donaldson matrix. The 2D matrix is an illuminant independent representation of the bi-spectral radiance factor. I introduced several measurement methods of the bi-spectral radiance factor. A two-illuminant projection method is useful in an ordinary scene using spectral imaging system. Finally, I showed the spectral imaging application to the appearance reconstruction problem.

### 3.18 Exploiting Human Eyes for Remote Sensing

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**Joint work of** D. Tuia, M. Volpi, B. Kellenberger, N. Rey, S. Joost

**Main reference** Rey, N.; Volpi, M.; Joost, S. & Tuia, D. “Detecting animals in African Savanna with UAVs and the crowds,” *Remote Sens. Environ.*, 2017, 200C, 341-351

**Main reference** Kellenberger, B.; Volpi, M. & Tuia, D.. Fast animal detection in UAV images using CNNs *IEEE International Geoscience and Remote Sensing Symposium, IGARSS, 2017*

**URL** <https://doi.org/10.1016/j.rse.2017.08.026>

Managing wildlife reserves is a complex task: rangers are confronted to poaching, livestock control and grazing needs estimation and often can use only manual counting requiring costly overflight or inaccurate land counts, followed by some extrapolation. In this talk, I present how we approached semi-automatic animals detection with computer vision technologies and images acquired by Unmanned Aerial Vehicles (UAV). I will discuss problems related to i) the acquisition of annotations using a crowd of volunteers; ii) the development of a wildlife detection system based on such annotation and a deep neural network and iii) the improvement of the databased using active learning approaches, also known as human-in-the-loop systems. The project is part of the SAVMAP initiative: <http://lasig.epfl.ch/savmap>.

### 3.19 Squeezing Spectra: Hot Topics at the Color Imaging Lab of the University of Granada

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**Joint work of** Miguel A. Martínez Domingo, Sergi Etxerebere, Juan L. Nieves, Javier Hernández Andrés, Javier Romero, N. Tello Burgos, A. López Montes

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Some of the topics that we have been working on at the Color Imaging Lab of the University of Granada are briefly introduced: detection of aging phase of indigo samples for an art-preservation related application; complete image pipeline for spectral High-Dynamic-Range Polarimetric images, including segmentation and material classification; and the improvement of saliency detection models when spectral features are used as input. These topics give rise to open questions related to bridging the gap between the art-preservation experts and ourselves, the use of spectral imaging as a seed bank for features that allow for simplification of the capture devices, and the possibility of using visual attention to improve the detection of regions of interest in the images to be further processed.

### 3.20 Optical Imaging Techniques for Non-contact Measurements of Vital Functions and Diagnosis of Tissues in Medicine

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© Rudolf Verdaasdonk, John Klaessens, and Herke Jan Noordmans

**Joint work of** VU University Medical Center, Medical Center Utrecht, Norwegian University of Science and Technology

In the recent years, CCD and CMOS camera technologies in the visible and near IR has opened new methods of diagnostics in medicine. For the mid-IR, thermal cameras have become small and practical with high spatial and temperature resolutions. With the introduction of practical 3D scanners, medical images have become quantifiable. New clinical applications were investigated, imaging dynamic changes in tissue perfusion, oxygenation and physiological processes to differentiate between healthy and abnormal tissues using combinations of narrow band spectral images. Near IR cameras were used to measure the heart and respiration rate in patients independent of skin tone and in dark conditions within 3% accuracy. Blood vessel puncture procedures were significantly improved visualizing the vessel structures on a screen like car navigation system. IR thermal imaging was applied successfully in cardiology (predict arterial spasm), urology (cause of impotence), anesthesiology (anesthetic block and pain treatment), aesthetic surgery (transplantation, burn wounds) and dermatology (allergic reactions) some in combination with 3D scanners. None-contact imaging techniques proved to be successful as new diagnostics tool that can easily be introduced in the clinic with minimal risk for the patient with great potential for general practitioners and even at home.

### 3.21 Introduction to THz Imaging and Spectroscopy

*Anna Katharina Wigger (Universität Siegen, DE)*

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**Joint work of** Gunnar Spickermann, Matthias Kahl, Christian Weisenstein, Daniel Stock, Peter Haring-Bolivar

Technology in the THz range is manifold as it is adapted from the neighboring domains in the electromagnetic spectrum. Many THz imaging systems have very low bandwidth and are to date not capable of materials recognition. THz spectroscopy is a very broadband technique to analyze material properties as the complex refractive index. The vision is a 3D THz imaging system, that covers multiple bands in real-time in order to recognize not only objects, but also can recognize materials directly.

### 3.22 Toward Practical Applications of High-Resolution Multispectral/Hyperspectral Video

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Joint work of Yuri Murakami

URL <http://www-oid.ip.titech.ac.jp/>

What are the issues toward widespread use of multispectral and hyperspectral imaging? Multispectral and hyperspectral imaging technology has been investigated in remote sensing, color imaging, and machine vision almost independently up to now and recently computer vision and machine learning field is also approaching to multispectral and hyperspectral technology. Gathering knowledge in different application fields is quite beneficial for promoting further commodification of the technology.

Firstly, it is important to explore the advantages of spectral imaging in a variety of fields, and we have demonstrated experimental results in color reproduction, medical image analysis, and human detection from airborne observation. Although the advantages of spectral imaging have been verified in various fields, there still exist serious issues that should be solved for practical use of spectral imaging. Since objects are moving in many cases, single-shot or video spectral imaging is crucial. However, it is still difficult to implement high-resolution spectral imaging with single-shot or video. As a solution to such issue, the approach of hybrid-resolution spectral imaging is illustrated. Finally, the significance of standardization-related activity for promoting practical applications is discussed. CIE (International Commission on Illumination) recently published a technical report “multispectral image format,” which has been prepared by TC8-07. CIE also establishes a new research forum “spectral imaging” and work items for promoting spectral imaging technology are now being discussed.

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### 3.23 Deep Learning in Remote Sensing

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**Joint work of** Xiao Xiang Zhu, Devis Tuia, Lichao Mou, Gui-Song Xia, Liangpei Zhang, Feng Xu, Friedrich Fraundorfer

**Main reference** Zhu X., Tuia D., Mou L., Xia G., Zhang L., Xu F., Fraundorfer F. 2017, Deep Learning in Remote Sensing: An Review, IEEE Geoscience and Remote Sensing Magazine, in press

**URL** <https://arxiv.org/abs/1710.03959>

In this talk, I intended to answer three questions:

1. What makes deep learning special in remote sensing?  
Keywords: five dimensional data, multi-modal data, big data, physical models etc.
2. Where we are today?  
Showcasing classification, change detection, data fusion, time series data analysis, and geo-info extraction from social media data
3. What are the open issues?  
Keywords: novel applications, transferability, very limited annotated data, benchmark, and combing deep nets with domain expertise.

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## 4 Working groups

### 4.1 Hyperspectral, Multispectral and Multimodal Image Acquisition

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**Joint work of** 10 attendees

Attendees participated in a workshop on hyperspectral image acquisition on Tuesday 10 Oct, 2017. The workshop was structured in two stages: first, a brainstorm establishing major topics, then a detailed discussion touching on the most important points. The following is a summary of the major points touched on during the discussion, followed by concrete recommendations.

## Manufacturers

A major challenge in effective acquisition is working with camera manufacturers. There are two key hurdles: first, communication from the manufacturers is often limited. They do not always clearly communicate the characteristics and limitations of their products. They also do not provide clear road maps outlining their intended future product developments, or a schedule for the release of calibration data and fixes to existing products.

The second issue comes in how we as a community can clearly communicate our needs to manufacturers. Ideally, we would dictate custom bands and resolutions on a per-camera basis, allowing applications to drive specific camera developments. Alternatively, it would be desirable to specify the needs of an application in terms of discriminative power, and allow the manufacturer to address these needs.

However, custom camera design is expensive and manufacturers are unlikely to address every request. The group concluded that there is an important market gap that would be addressed by an easily customised multispectral camera. We acknowledged that Pixeltrek offer custom, possibly costly colour filter arrays (CFAs), and that colour filter wheels can go some way to addressing this challenge, but there seems to be a remaining market gap in providing affordable custom snapshot multispectral cameras.

## Calibration

Calibration was identified as a major common concern. This includes radiometric, geometric, and spectral characterisation. There are open questions as to how good a calibration needs to be, and indeed, what the limits are on how good a calibration can be. There are some applications, e.g. satellite and retinal imaging, for which complete calibration seems impossible as it would require direct knowledge of the medium (air, eye lens and vitreous).

In some instances blind calibration may be possible based on prior knowledge of the manifold of physically viable media. The motivating example arose of obtaining a calibrated colour measurement of the back of the eye. There is an unknown spectral impact from the eye's lens, which is variable between individuals and yellows as we age. Suggestions arose around measuring scattered light as a hint of the lens' impact, and characterising the manifold of spectral characteristics typical of human eyes. This could be driven by physically based modelling given knowledge of the source of yellowing in the eye's optics. Then the inverse problem of separating the lens colour from the colour of the back of the eye can be carried out as an optimisation subject to the constraint of physically feasible lens and eye colours. The possibility was also raised that structured light or other coded illumination may be able to disambiguate the colour of the lens from that the back of the eye.

The group discussed whether calibration procedures are sufficiently well defined and universally understood. It was generally held that that spectral calibration is fairly well defined and understood, if tedious, but that radiometric (gain) calibration is not as well defined, and often overlooked. This kind of calibration is time-consuming and not every lab has the capability. Sharing of calibration capability is difficult, expensive, and time-consuming, taking up to a week to calibrate a single sensor.

One concrete recommendation is that calibrations for commercial products be openly shared. Present datasets are spread out, and there is a call to collect these and provide a centralised location for the community to share calibration information and procedures.

### Novel Optical Setups

We discussed at some length a set of emerging technologies in hyper- and multi-spectral capture. One set of techniques split the camera's field of view into multiple sub-images, employing filters to turn each sub-image into a separate colour band. This is essentially a light field camera with per-subaperture colour bands, and it might benefit from combining concepts from light field imaging and hyperspectral imaging.

Further ideas on the camera side included coded aperture snapshot spectral imaging (CASSI), custom CFAs including masks that combine colour and polarisation, a NASA-developed holographic multispectral camera, tuneable filters, and microprism arrays for on the order of 100 colour bands with low spatial resolution (order  $100 \times 100$  pixels).

Further ideas concerned the use of novel lighting arrangements, employing multiple LEDs with diffusers. A concern with these configurations is obtaining sensitivity outside the visual spectrum, and getting IR and other bands to cooperate on a camera with no IR cut filter. Tuneable lighting came up as another option, with the caveat that calibration can be difficult.

We discussed the chicken-and-egg problem of camera design and applications: it is difficult to motivate fabrication of custom cameras before having a strong idea of their application, and conversely it is difficult to demonstrate applications of novel cameras without building them. The question of optimal sensor design came up, and discussion touched briefly on the use of information-based metrics vs. deep learning to address the complex statistics of visual perception.

### Lossless Low-Level Processing

Conversation touched on the line lies between raw data, pre-processing, and processing. Often in conventional imaging the impact of demosaicing is neglected, and not considered part of the processing at all. However, without storing additional information this step is destructive, even in the simple case of an RGB camera. In the multi- and hyper-spectral cases things are more complex and the potential for loss of information between steps is strong. There was a consensus that there is a need for more standardised interfacing between levels of processing, and that there is a need for stronger intermediary image representations and file formats. In particular, images should include whatever information is available on the CFA bands, noise levels, exposure, channel alignment, radiometric calibration, and ultimately covariance of demosaiced and processed colour. Ideally, one should be able to reconstruct the raw imagery using the pre-processed imagery and accompanying metadata. We presently lack a universal format with which to allow this level of lossless processing.

### Recommendations

The discussion yielded a set of concrete recommendations. For calibration data, there is a need to collect existing calibrations into one place, and to work towards standardising calibration procedures to increase the value of shared calibrations. When dealing with manufacturers be specific and aggressive when asking for calibration information. Manufacturers should provide (and be encouraged to provide) roadmaps of what they plan to calibrate and fix in future. A survey paper covering existing calibration methodologies would be well received by the community.

There is a market gap for an easily customized multispectral camera, allowing application-specific cameras to be quickly customised, evaluated, and deployed.

There is a need for a common file format including metadata at the interface between pre-processing and processing. This should provide, for example, covariance of demosaiced

colour, CFA bands, noise levels, exposure, and any available calibration information. There is ideally sufficient information in any pre-processed image to infer the RAW imagery that yielded it.

While presenting an overview of this discussion to the larger group, we identified as an action item follow-up discussion on the potential of CIE file formats for hyperspectral imagery.

## 4.2 Deep Learning for Analysis of Multispectral Data

*Dietrich Paulus (Universität Koblenz-Landau, DE) and Richard Bamler (DLR - Oberpfaffenhofen, DE)*

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**Main reference** J. Johnson, A. Karpathy, and L. Fei Fei. “Densecap: Fully convolutional localization networks for dense captioning.” In CVPR16, pages 4565–4574, 2016

**Main reference** R. Kemker and C. Kanan. “Deep neural networks for semantic segmentation of multispectral remote sensing imagery.” In CoRR, abs/1703.06452, 2017

**Main reference** W. Shen, X.G. Wang, et al. “Deepcontour: A deep convolutional feature learned by positive-sharing loss for contour detection.” In CVPR15.

The discussion mainly focused on deep learning (DL) for remote sensing.<sup>1</sup>

Other aspects, such as other machine learning (ML) methods and other applications for multispectral image analysis (such as multispectral cameras on vehicles) have been only partially addressed.

### General Statements on Deep Learning

Many papers are published in remote sensing journals making use of deep learning - but not really doing research in deep learning.<sup>2</sup> The reason might be, that ML people were often not interested in applications. Researchers in remote sensing had to do research combining ML methods and the application.

In general, there seems not to be enough labeled or ground-truth data – at least in remote sensing – to train large neural networks. This is a big difference to computer vision tasks, where large sets of annotated images exist.<sup>3</sup>

In the following are statements pointed out during the working group session:

1. DL has proven to be superior to other ML methods in detection and classification (labeling).
2. It is not clear yet how DL performs in quantitative parameter estimation from spectral measurement data.
3. The understanding of what really happens in a deep neural network (DNN) is underdeveloped. A lot of progress is achieved by “trying out”. If trying replaces understanding, is this still in agreement with our understanding of science?
4. DL can potentially help for building up efficient dictionaries, e.g., for sparse reconstruction.
5. We do not know at the moment how prior knowledge can be incorporated into DL in a systematic way.

<sup>1</sup> A survey on these methods was also given in the presentation of X. Zhu.

<sup>2</sup> Of course, studying the structure and performance of deep neural nets can also be considered research in this field.

<sup>3</sup> This has also been claimed in <https://arxiv.org/abs/1703.06452>, see also (Kemker and Kanan).

6. It is difficult to obtain a quality measure (error bar, covariance matrix, etc.) of results obtained by DL.
7. To the knowledge of the group DL is currently mostly restricted to “image-type data in – image-type data out”. One exception are applications, that generate figure captions from images, see (Johnson, et al). This is an example, where structured symbolic data is computed from an input image.

Nevertheless, in the following are several questions that were raised and remained without answers:

1. Are there e.g. successful examples for vectorization of input images by DL?<sup>4</sup>
2. Do we have to throw away human expertise when we use DL?

### Big Problems Solved by Machine Learning

The following areas have been identified where solutions by ML (in the context of analysis of multispectral data) have been published: Detection, classification, super-resolution, enhancement, fusion, change detection, and image restoration. Whether or not these areas can be regarded as “solved” needs to be discussed.

### What has not been possible up to now with ML

Find something new in visualization.

## 4.3 User Involvement, Validation Tools, Data, and Software Sharing

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Joint work of 10 attendees

### User involvement

The workshop attendees represent mostly research institutes from the HMM field. However, it is important to identify the end users of HMM technology and get them involved in the development of hardware and application software. The following are the fields or end users of HMM technology identified during the working group session: Physician in the medical field, heritage of artifacts and art, military, ecologists, earth observation: drones and satellites, metrology, garbage recycling, food industry, cosmetics, security, autonomous driving, agriculture, and emergency services.

The end users are usually less interested in the HMM technology but just the results it can provide for their needs/ goal. The results/ data should be presented to the user in an intuitive way with similarity to regular presentations in their workflow. The success of acceptance of new HMM technology will depend on the user friendliness of the systems and presentation of results. The needs of end users of HMM technology themselves are, e.g., quantification, segmentation of materials, tissues, and structures, specifications of materials, and detection.

Methods of presenting HMM data to the user:

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<sup>4</sup> For computer vision problems, results have been published in (Shen, et al).

- Data fusion in existing visualization methods
- Presenting data in color palettes which are intuitive for the user
- Blinking or blending
- Superposing/ mixing on visual/ original image with adjustable transparency (see example at [iipimage.sourceforge.net](http://iipimage.sourceforge.net))
- In contrast with background
- Selection of preset filters like highest and lowest values

Important aspects regarding the acceptance of new HMM technology:

- Communication with user is important
- Cost effective
- Fit in the normal workflow
- System should be mobile and flexible

Regarding the opportunities to open consumers market for HMM technology, if there would be consumer driven need for HMM technology, sensors would be made in mass production and the price would drop enormously, e.g., HMM sensor in a smart phone. In the following are several ideas for potential applications:

- Detection of mushrooms eatable or poisonous
- Food/ meat/ fruit freshness detection in supermarket
- Presences of potential toxic substances on food
- Cosmetics: Color of foundation and make-up
- Color of cloths under different lighting conditions
- Dentist: color of restorations or crowns, check in other light conditions
- Check on health of pets/ animal
- Combinations with thermal camera
- Combination with time of flight sensor (from automotive industry)
- Hair salons: Color prediction before hair dye
- Recognition of materials
- Characteristics of light sources at home in relation to the perception of paint on the walls
- Automotive industry

As a remark, consumer market is different from the needs for accurate measurements in scientific community.

### Sharing HMM data sets and software

Within the HMM research community, there is a need for benchmark data/ images for validation and testing software algorithms. It is important to set the rules by the leading people how the dataset can be used and the proper way to refer to data set in publications. Especially, the users need to pay attention to the ground truth when they analyze the data and always make a comparison. The data should be made available through a website. Which organization/ institute could host a website for this? In the following are several of the considerations:

- One organization/ person should be made in charge/ responsible for website. CIE could potentially take the initiative but does not have resources.
- As other options: To join with websites already hosting other datasets, create own website with a wiki page like layout to allow relatively easier maintenance. Another option is also to have a website with links/ torrent to source of original data
- Regarding the data sharing, the ones that are easily available will be small samples while the larger while could be downloaded later

- Example website: Data fusion contest (IEEE) with open data sets available, or the color constancy website

### **Phantom/reference for testing and validation**

There is a need for a test target/reference/phantom to be able to compare and/or validate data from various HMM systems like a 3D physical ‘color checker’ with various properties like translucency, texture, angle of illumination etc. Example Round Robin Test: reference objects (color checker, paintings, etc.) for MSI where distributed along universities over the world for testing there MSI setup. The result showed that there was a large range in outcome in spectra, not reproducible without a protocol describing the conditions to perform the test. There is much to improve on this topic.

### **Synthesis and Analysis**

Regarding the software or standard algorithms, there is a need for a software platform with algorithms for sharing, comparable to the computer graphics field where standards have been implemented. As potential software platforms are ‘Vision’ and ‘PKLF’. The latter have been proposed as a standard in the past.

Besides sharing the software and algorithms, it is important that the data file should be readable by the software. Thus, the need for standard file format for HMM data. Points discussed during the session were: Which institution should be responsible for the task and which software platform. Matlab is generally not preferred because of non-compatible versions and as it is commercial. Python could be chosen as an alternative.

A website could be the solution, combined with data sharing as discussed in the previous sections. But then again, there is still the question of which institution could host such a website. Although one from the computer science community is more preferable. A remaining discussion point was related to the role/ task the stakeholders such as manufacturers should take.

Finally, aside from all the tasks and challenges that have been identified above, there are already many of the success stories. Moreover, what can be learned from those areas/ users where HMM technology is already accepted or proven successful are, i.e., it is important to be close with the users, to understand their environment and talk with the same language. Such success stories can be found in the areas of dentistry, automotive industry, several medical applications, checker for the health of seeds, earth remote sensing, security such as in airports (milli-/ terahertz), and biometrics.

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