Chapter 2
User Information Needs

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Abstract Computer vision technology has been considered in marine ecology research as a innovative, promising data collection method. It contrasts with traditional practices in the information that is collected, and its inherent errors and biases. Ecology research is based on the analysis of biological characteristics (e.g., species, size, age, distribution, density, behaviors), while computer vision focuses on visual characteristics that are not necessarily related to biological concepts (e.g., contours, contrasts, color histograms, background model). It is challenging for ecologists to assess the scientific validity of surveys performed on the basis of image analysis. User information needs may not be fully addressed by image features, or may not be reliable enough. We gathered user requirements for supporting ecology research based on computer vision technologies, and identified those we can address within the Fish4Knowledge project. We particularly investigated the uncertainty inherent to computer vision technology, and the means to support users in considering uncertainty when interpreting information on fish populations. We introduce potential biases and uncertainty factors that can impact the scientific validity of interpretations drawn from computer vision results. We conclude by introducing potential approaches for providing users with evaluations of the uncertainties introduced at each information processing step.

2.1 Introduction

Requirements for the scientific study of fish population concern both (i) the kind of *measures* that need to be performed for specific studies (Table 2.1), and (ii) the *sampling method* i.e., the conditions under which measurements need to be performed (e.g., repeating measurements at timeframes, locations, or other environmental

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conditions of interest). The Fish4Knowledge project developed technologies providing *measurements* of fish populations. Provided with such technology, ecologists can study fish populations at the locations or periods of interest, applying the *sampling method* appropriate for their study.

Measurements are never perfect, whether they are performed with novel computer vision technology, or with more traditional data collection techniques. They contain errors such as misidentified species or undetected fish. The *sampling method* can be an additional source of uncertainty. For instance, too few measurements may be performed on benthic zones (i.e., ecosystems on the sea floor). The information needs and uncertainty issues related to *sampling methods* were not in the scope of the Fish4Knowledge project, and are only briefly discussed in this chapter. We refer to Cochran (1977) for further information on sampling methods.

In this chapter, we discuss the kind of *measurements* that can be performed through computer vision. We first introduce the essential measures for ecology research on fish populations (Sect. 2.2), and the data collection methods that can provide such measurements (Sect. 2.3). We detail the biases at stake with computer vision compared to other data collection methods in Sect. 2.4. Finally, Sect. 2.5 discusses the uncertainty factors involved when applying our computer vision technology. It considers uncertainty issues arising both with the computer vision algorithms, and with the in-situ application conditions (e.g., the impact of fields of view and image quality on computer vision uncertainty). It introduces the information needs for controlling the uncertainty in computer vision results.

2.2 Information Needs for Ecology Research on Fish Populations

A large variety of ecology studies rely on monitoring fish populations. For instance, monitoring fish populations takes part in studies that aim at describing ecosystems' typology (e.g., types of habitats, distributions of animal and plant species, and feeding habits i.e., *trophic* chains), evaluating differences between ecosystems under different conditions (e.g., before and after environmental events such as typhoons, or human disturbances such as construction works), or investigating specific characteristics of species (e.g., daily routines, reproduction seasons, and maturity phases). Across this variety of topics, most studies rely on similar measurements performed on fish populations, and on similar sampling methods to decide on when and where to perform the measurements.

Measuring fish populations—The most basic measures of fish population are fish counts and species identification (Gibson et al. 2001; Magurran 2004). With this information, ecologists investigate questions such as how many fish occurred in specific time periods and locations, what were their species, what is the proportion of each species in the overall population (i.e., the *species composition*), what is their distribution and density over areas, or what is the total number of species

Table 2.1 Information required for studying aspects of population dynamics, and ability of data collection methods to extract the necessary information

	Fish counts	Species identification	Behavior identification	Fish body size
Research topic				
Population dynamics	Mandatory	Mandatory	Optional	Important
Trophic systems	Mandatory	Mandatory	Important	Important
Reproduction	Mandatory	Mandatory	Important	Important
Migration	Mandatory	Mandatory	Optional	Optional
Data collection method				
Experimental fishery	+	+/ ++[a]	−	++
Commercial fishery	+	+	−	+
Diving observation	+	+	++	+
Manual image analysis	+	+	+	−/+[b]
Computer vision	+	+	−/+[c]	−/+[b]

The signs indicate whether data collection methods: − cannot supply the information, + can supply the information, ++ can supply the most precise information

[a]Fish dissection, sometimes performed after experimental fishing, is the most accurate technique for recognizing coral reef species that are visually similar

[b]Information supplied if stereoscopic vision, or calibrated distance camera-background

[c] The state-of-the-art does not fully address the wide scope of fish behavior variety

(i.e., the *species richness*). Other widely-spread information needs are fish body size and behavior identification. From fish body size, ecologists derive fish age and maturity, as well as reproductive cycles (e.g., presence of offspring). From fish behavior (e.g., mating, feeding, nursing, aggressiveness), ecologists derive fish maturity and reproductive cycles too, but also seasonal cycles and food chains (i.e., *trophic systems* describing which species feed on which species, and how often). User information needs concern the study of population dynamics in general, i.e., how species abundances evolve over time, locations or environmental conditions. They also concern the study of three main phenomena influencing population dynamics: trophic systems, reproduction and migration. Each topic of study requires specific information, as summarized in Table 2.1. These user information needs are illustrated in Table 2.2 with typical questions ecologists seek to answer with our video monitoring system.

Sampling method—All studies require a correct sampling of fish counts for the species, time periods and locations of interest. For some studies of reproduction and migration, an extensive sampling of large areas and time periods covering one to several years is necessary. Sampling methods are well-developed in the ecology domain (Cochran 1977). Requirements for appropriate sampling basically consist of collecting information for subsets of locations and time periods that are representative

Table 2.2 Typical questions ecologists seek to answer (Deliverable 2.1 (Beauxis-Aussalet et al. 2012))

Q1	How many species appear and their abundance and body size in day and night including sunrise and sunset period
Q2	How many species appear and their abundance and body size in certain period of time (day, week, month, season or year). Species composition *[set of species and relative population sizes]* change within one period
Q6	Feeding, predator-prey, territorial, reproduction (mating, spawning or nursing) or other social or interaction behavior of various species
Q7	Growth rate of certain species for a certain colony or group of observed fishes
Q8	Population size change for certain species within a single period of time
Q10	Immigration or emigration rate of one group of fish inside one monitoring station or one coral head
Q11	Solitary, pairing or schooling behavior of fishes

of the overall ecosystem. Ecology research typically considers the different components of ecosystems, e.g., the types of habitats and their proportional land coverage. Samples are often collected in each part of the ecosystems, proportionally to their geographical coverage (i.e., *stratified random sampling* in Cochran 1977). Measurements are repeated to account for their variance. Measurements' variance contributes to the interpretation of the patterns observed in the collected data. Well-founded statistical methods, based on measurements' variance, allow to compute the probability that patterns observed in the data occurred by chance, and are not representative of the actual fish populations. These statistical methods are essential for ecology research, since they support the scientific validity of conclusions drawn on fish populations.

2.3 Data Collection Techniques

Computer vision is a relatively new technique for marine ecology. Marine ecologists traditionally rely on 3 main data collection techniques: experimental fishery, commercial fishery data, and diving observations. Additionally, the use of cameras has been rapidly developing as a promising technique.

Experimental and commercial fisheries—For experimental fishery, scientific vessels are used to catch fish at specific sampling locations and time periods, with calibrated nets or fish traps. Ecologists then perform measurements which sometimes include fish dissection. For collecting data from commercial fishery, two methods exist: data can be collected by ecologists onboard commercial vessels, or by non-scientific personnel of the fishery company. The latter involves trust issues and potential biases due to the experience of the person in charge of collecting the data (Kraan et al. 2013). Commercial fishery data have the advantage of offering large coverage of marine areas, but at the disadvantage of targeting only commercial species.

Diving observations—Divers can collect further information complementing fish counts and species identification. A variety of fish behaviors can be observed, whereas fishery data can only provide information of feeding and reproductive behaviors (e.g., through fish dissection revealing the content of fish stomach or the presence of offspring and eggs). Further, cryptic and benthic species (i.e., camouflaged or living on the seabed) are better sampled since they are unlikely to be caught in fishing nets. However, diving observations cannot provide perfect data as human observers can make mistakes, e.g., depending on their diving experience, or difficulties inherent to fish species or ecosystems.

Video technologies—Images are also widely used as a means of observation. Cameras are used at fixed locations, with or without baits attracting fish. They can be oriented toward the open sea, or toward the sea floor for sampling benthic ecosystems. For the latter, calibrating a fixed distance between cameras and sea floor allows the measurement of fish body size. Stereoscopic vision, i.e., the use of pairs of cameras, is a more precise technique for estimating fish body size. Divers also use handheld cameras, sometimes moved along transects (i.e., predetermined path on the sea floor covering a representative part of the ecosystem). Recent innovations in ecology practices particularly developed on Stereo Baited Remote Underwater Video systems (stereo-BRUV), where stereoscopic vision allow the measurement of fish body size (Langlois et al. 2006). Figure 2.1 shows examples of handheld and stereo-BRUV cameras.

Ecologists visually identify the fish and their species, and interpret their behavior. Computer vision has valuable potential as a replacement of tedious, time-consuming manual image analysis. The development of this technology can aim at extracting the same scope of information as for manual image analysis. To address user information needs, the primary computer vision task is the detection of fish and their species (see Chaps. 9–11). For behavior identification, the Fish4Knowledge project is supported by recent research addressing the detection of rare and abnormal behaviors (see Chap. 12). The project also benefit from experimentation with a behavior

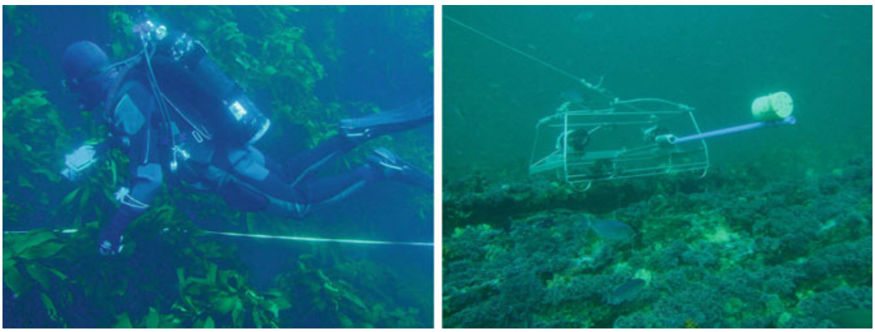

Fig. 2.1 Example of handheld (*left*) and stereo-BRUV cameras (*right*). Photography by Peter Southwood, licensed under Creative Commons Attribution, “Diver swimming a transect for Reef Life Survey PB164684” (*left*), “Stereo BRUVS in action at Rheeders Reef P2277038” (*right*)

identification technique based on user-defined rules, and potentially applicable for collecting ground-truth sets of fish behaviors (Spampinato et al. 2013). But further technical challenges need to be addressed since the scope of fish behaviors is very diverse. For instance, the visual features representative of fish behaviors are difficult to specify. They vary depending on species for the same behavioral functions (e.g., each species feeds differently), and they often need to be analyzed overtime in several video frames, since some behaviors are not recognizable in a single image.

Impact of video technologies on sampling methods—Estimating the area covered by the cameras' field of view is essential to the design of sampling methods, and to the analysis of the collected data (e.g., to study fish density). But estimating the area covered by a camera is a difficult task. For instance, it requires controlling the distance within which information collection is possible, or is reliable enough (e.g., for detecting small fish). Such depth of field of view varies depending on camera lens, image quality, water turbidity, and the reliability computer vision software. Estimating the area covered by cameras is more subtle when baits are used. The strength and direction of currents modify the area in which animals can sense the bait, and thus the coverage of the sampled area (Taylor et al. 2013).

The use of fixed cameras, with continuous collection of measurements on fish population, is an important paradigm shift regarding the temporal coverage of the samples. It contrasts with common data collection methods that perform measurements during limited timeframes. Their temporal coverage is limited to the selected timeframes, and the measurements performed within a timeframe are intended to represent all the species living in the environment. With the Fish4Knowledge system, the temporal coverage is very large, with fish counts continuously measured over time. More precisely, since video streams are sequenced and stored and 10-min video samples, fish counts are repeatedly measured in small units of time, i.e., every 10 min. Ecologists can not assume that measurements performed on a 10-min video sample are representative of all the species living in the ecosystem. But they can assume that species occur in videos samples at their natural frequency.

Scope of the Fish4Knowledge project—Each data collection method has its own advantages and disadvantages, and no single method fits all types of ecology research. The requirements for selecting a data collection method comprise constraints on the types of ecosystem to access, the timeframes for performing the study, the human and material resources available, the funding for acquiring and maintaining equipments, the types of information that need to be collected, the measurements' potential errors and biases, and on the uncertainties that can be tolerated. The most important information needs, as summarized in Table 2.1, are addressed by a choice of data collection techniques. Computer vision potentially provide measurements of fish body size. But the Fish4Knowledge project was not provided with equipments for measuring it (e.g., stereoscopic vision). Detecting fish behavior is supported by advances such as those presented in Chap. 12 and Spampinato et al. (2013). But the large variety of fish behavior is seldom addressed. For instance, it is challenging to detect all the diverse feeding behaviors of a small set of species. Hence the Fish4Knowledge user interface focused on addressing two main user information needs: fish counts and species identification. With this information, ecologists can study population dynamics, i.e., the evolution of fish counts over time, locations, or other environmental conditions. Migrations and reproduction cycles are possible to study, on the condition of implementing an extensive sampling of the ecosystem. The next sections detail the potential errors and biases inherent to computer vision, and the related information needs for controlling the uncertainty issues.

2.4 Potential Biases

All data collection methods are imperfect and can yield errors and biases in measurements of fish populations. Some errors can be systematic and yield biased information, e.g., some species are potentially over- and under-represented. For example, cryptic species camouflaged amongst corals are typically under-estimated in fish counts because they are more difficult to detected. Data collection methods are thus always *selective*, i.e., specific parts of ecosystems and specific species are not consistently measured and their measurements are biased. From comparative studies of data collection methods (Cappo et al. 2004; Harvey et al. 2001; Lowry et al. 2012; Trevor et al. 2000) and from interviews with ecologists, we identified nine main forms of *selectivity* at stake with the common data collection methods discussed in Sect. 2.3. Data collection methods potentially bias the counts of nine types of species: *benthic* species (i.e., living on the sea floor), *sedentary* species (i.e., living in and around the cavities of coral heads), *schooling* species (i.e., living in dense groups), small species and young fish, *cryptic* species (i.e., camouflaged in the ecosystem), *shy* species (i.e., fleeing humans and boats), *look-alike* species (i.e., visually similar species), *rare* species (i.e., occurring at low frequency), and herbivorous or carnivorous species. Table 2.3 summarizes the potential biases implied by the main data collection methods. The Fish4Knowledge project uses cameras without bait, at fixed positions and not held by divers, and that can be positioned to observe benthic zones and coral heads. These settings limit potential biases in the counts of benthic, sedentary, shy, herbivorous and carnivorous species. Yet, biases are still at stake with sedentary, schooling, cryptic, look-alike and rare species, as well as small fish.

Sedentary and schooling species—Computer vision potentially over-estimates sedentary and schooling species because they are likely to repeatedly swim in and out of the camera field of view. Hence single individuals may be repeatedly counted. For instance, with our system, we observed potential over-estimation of a sedentary species called *Dascyllus reticulatus*. Schooling species may as well be under-estimated because fish in the group occlude each other and may remain undetected.

A method to overcome such biases with sedentary and schooling species consists of counting fish appearing in only one frame of the video footage. But this method is likely to further under-estimate rare species, since the chances they appear on one single frame are very low. Further, this method disables the analysis of visual features over several frames (e.g., fish trajectories) which is necessary for recognizing fish behavior, and identifying some species (i.e., if their swimming behavior is more discriminative than their visual appearance).

Table 2.3 Main biases with species that are potentially under- or over-estimated by data collection methods

	Experimental fishery	Commercial fishery	Diving observation	Manual image analysis	Computer vision
Benthic species	–[a]	–[a]	=	=	=
Sedentary species	–	–	=	=	= /+[b]
Schooling species	=	=	–/+	–/+	–/+[b]
Small fish	–/ =[c]	–/ =[c]	–/ =[d]	–/ =[d]	–/ =[d]
Shy species	–	–	–/ =[e]	–/ =[f]	–/ =[f]
Cryptic species	–	–	=	–	–
Look-alike species	=	=	–/+	–/+	–/+
Rare species	=	–	=	=	–/ =[g]
Herbivorous and carnivorous species	–/ =[h]	=	=	–/ =[h]	–/ =[h]

The signs indicate whether parts of ecosystems are likely to be + over-represented, = neither under- nor over-represented, – under-represented.
[a]Considering that the destructive use of trawl nets is not an option
[b]Some species often swim in and out of the camera field of view, yielding over-estimated fish counts
[c]Large granularity of nets' and fish traps' mesh can let small fish slip through
[d]Small fish may not be visually detectable from a large distance
[e]Cloaking procedures can allow the observation of shy fish
[f]With handheld cameras, some species flee from divers
[g]The recognition of all rare species may not be possible due to lack of ground-truth images
[h]Baits, if used, can attract either herbivorous or carnivorous species

Small fish—Detecting small fish is difficult for all data collection methods in Table 2.1. In the case of diving observation, manual image analysis and computer vision, this type of bias is limited if observations are performed within small depths of field of view. With large depths of field of view (e.g., observing the open sea), ecologists need to consider that small fish are sampled only in a limited range around cameras or divers.

Look-alike and cryptic species—Look-alike and cryptic species are difficult to detect for computer vision software and human observers. Look-alike species can be either over- or under-estimated, and cryptic species are very likely to be under-estimated. Ecologists need to apply specific methods for studying cryptic species. These involve either divers carefully scrutinizing sea floors or coral heads, or the use of toxicants forcing the fish to leave their camouflaged position. Data collection based on imagery is not suitable for their study.

Rare species—Under-estimations of rare species is due to the inability of computer vision software to recognize species for which there are insufficient image samples to train the recognition algorithm. This can be overcome by implementing the missing species recognition features, at the cost of collecting ground-truth for these species. More information on ground-truth collection requirements are discussed in Chap. 14.

2.5 Uncertainty Factors Impacting the Potential Biases

Ecologists are concerned with the reliability of information extracted using computer vision technologies. User needs for information on uncertainty issues are illustrated in Table 2.4 with typical questions ecologists seek to answer. Considering the entire population monitoring system, potential errors and biases are not only due to computer vision software. Uncertainty is also introduced throughout the in-situ deployment of the system. For example, some cameras may receive lower lighting, and yield poor image quality and more computer vision errors. For the Fish4Knowledge system, its in-situ deployment (see Chaps. 3–8) and its computer vision software (see Chaps. 9–11), we identified the 10 uncertainty factors summarized in Table 2.5.

Uncertainty factors due to computer vision software—The computer vision algorithms developed within the Fish4Knowledge project use sets of fish examples to learn how to detect fish and species, called ground-truth. They are manually annotated by experts, and often crowd-sourced (see Chap. 14). *Ground-Truth Quality* is essential to control the errors in computer vision results. Scarcity, *Image Quality* or annotation errors in ground-truth images potentially yield error-prone computer vision software. The Fish4Knowledge system processes images in two steps, fish detection and species recognition. *Fish Detection Errors* concern undetected fish (i.e., False Negatives) and non-fish objects identified as fish (i.e., False Positives). *Species Recognition Errors* concern species misidentifications, i.e., fish recognized as a species they do not actually belong to. *Fish Detection Errors* can impact *Species Recognition Errors*, i.e., species can be attributed to non-fish objects.

Table 2.4 Typical questions ecologists seek to answer w.r.t. uncertainty issues (Deliverable 2.1 (Beauxis-Aussalet et al. 2012))

Q13	In certain area or geographical region, how many species could be identified or recognized easily and how many species are difficult. The most important diagnostic character to distinguish some similar or sibling species
Q16	Comparison of the different study results between using diving observation or underwater real time video monitoring techniques. Or the advantage and disadvantage of using this new technique
Q17	The difference of using different camera lens and different angle width
Q20	Hardware and information technique problem and the possible improvement based on current technology development and how much cost they are

Table 2.5 Uncertainty factors introduced by computer vision software or in-situ system deployment

Factor	Description
Uncertainty due to computer vision algorithms	
Ground-truth quality	Ground-truth items may be scarce, represent the wrong objects, or odd fish appearances unlikely to yield representative fish model
Fish detection errors	Some fish may be undetected, and non-fish objects may be detected as fish
Species recognition errors	Some species may not be recognized, or confused with another
Uncertainty due to in-situ system deployment	
Field of view	Cameras may observe heterogeneous, incomparable ecosystems. Fixed cameras may shift overtime (e.g., with typhoons, maintenance)
Duplicated individuals	Fish swimming back and forth are repeatedly recorded. Rates of duplication vary among *Fields of view* (e.g., open sea or coral head) and species swimming behavior (e.g., sheltering in coral head), thus producing biases
Sampling coverage	The numbers of video samples collected for each condition of interest (e.g., areas, time periods) may not be sufficient for the statistical validity of conclusions derived from software outputs
Fragmentary processing	Some videos may be yet unprocessed, missing, or unusable (e.g., encoding errors)
Uncertainty due to both computer vision algorithms and deployment conditions	
Image quality	Recording conditions may impair [the] collected information, e.g., lighting conditions, turbidity, lens fouling, resolution, frame rate and compression
Biases emerging from noise	Data processing errors may be random (noise) or systematic (bias). Biases may emerge from the combined features of data collection (*Image Quality, Field of View*) and processing (*Fish Detection* and *Species Recognition Errors*)
Uncertainty in specific output	Errors in specific computer vision results may be extrapolated from errors measured in test conditions, compared to the conditions specific to subsets of computer vision results (*Image Quality, Field of View*)

Uncertainty factors due to in-situ deployment conditions—This source of uncertainty is usually not in the scope of computer vision software evaluations. Evaluations performed in computer vision research are intended to be valid for most applications of the algorithms, and are abstracted from case-specific application conditions. However, errors and biases in computer vision outputs can be significantly influenced by environmental conditions (e.g., water turbidity lowers *Image Quality* and may increase *Fish Detection Errors*), by the placement of cameras (e.g., some *Fields of View* may over-represent sedentary species), and by computational issues during video processing (e.g., missing videos yield *Fragmentary Processing*).

The uncertainty factors introduced when deploying the system interact with each other, and with the uncertainty factors inherent to computer vision algorithms.

The *Field of View* impacts the kind of ecosystems observed by each camera, as well as the size of areas within field of view depth. Hence it influences the *Sampling Coverage*. *Field of View* also impacts the chances of *Duplicated Individuals*, e.g., observing coral heads is more likely to yield overestimation of sedentary species than observing the open sea. The *Image Quality* of recordings is impacted by both camera features (e.g., lens), and time-varying environmental conditions (e.g., lighting, turbidity, biofouling). Different *Image Quality* can yield different levels of *Fish Detection* and *Species Recognition Errors*, and thus potential *Biases Emerging from Noise*. Finally, the initial *Sampling Coverage* allowed by the camera deployment over the ecosystem can be reduced by *Fragmentary Processing* of the videos, i.e., due to unprocessed or missing videos.

2.6 Conclusion

Computer vision technology has a great potential for ecology research. It can address essential information needs, while reducing the material cost and human effort involved with common data collection techniques. However, information extracted from video is not perfect, and for scientific usage, evaluations of uncertainty must be delivered to ecologists. The Fish4Knowledge project needs to addresses the challenge of providing both information about fish populations (Table 2.1), and about the uncertainty inherent to the computer vision system. The project needs to deliver fish detection and species recognition algorithms, to provide essential information for studying fish population dynamics, and potentially, for studying fish migration, reproduction and trophic systems (i.e., food chains). The project also needs to provide evaluations of the errors in fish detection and species recognition. It supports ecologists in estimating potential biases in computer vision end-results. Ecologists need to consider other uncertainty factors, such as image quality or missing videos. Means to assess and communicate uncertainty issues to ecologists are discussed further in Chaps. 13 and 15. Integrating information about these uncertainty issues is necessary to enable the scientific usage of Fish4Knowledge technologies.

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