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Original Article

Video capture of crustacean fisheries data as an alternative to on-board observers

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For EU member states to meet the requirements of the Marine Strategy Framework Directive and the reformed Common Fisheries Policy, it will be necessary to improve data collection related to many fisheries that are at present subject to relatively little monitoring or scientific research. This study evaluated the use of on-board camera systems to collect data from *Cancer pagurus* and *Homarus gammarus* fisheries. We evaluated the reliability of the hardware and its ability to collect images of sufficient accuracy and precision compared with using on-board observers. Fishers and on-board observers passed animals removed from traps across a defined area. The relationship between the *in situ* and predicted measurements of carapace length of lobsters or carapace width (CW) of crabs was investigated. The mean difference between the predicted and real crab measurements was −0.853 mm with a standard error of 0.378 mm. Suggesting that the model tends to underestimate the real CW slightly. The mean difference between predicted and real data for lobsters was 0.085 mm with a standard error of 0.208 mm. Sex allocation for crabs based on video images was 100% accurate. All male lobsters were correctly assigned. For lobsters >86 mm in length, the correct female sex allocation was 100% accurate. For smaller lobsters, the accuracy of sex allocation decreased to a low of 51% in lobsters <70 mm. Camera systems were found to be a suitable method for collecting data on the size and sex of crabs and lobsters. The error attributable to using video data rather than manual measurement was less than 3 mm, which is sufficient to detect growth increments in these species. The requirements to collect basic species data are increasing and the ability to do so without on-board observers will reduce the cost implications of these requirements. Future computer automation of image extraction and measurements will increase the application of video systems for data collection.

Keywords: crabs, fishery-dependent data, image analysis, lobsters, Marine Strategy Framework Directive, self-sampling.

Introduction

Fishery-independent surveys are commonly used to supplement data derived from fisheries-dependent data. Typically, these surveys are restricted to commercially important (quota) species that are managed using a variety of effort controls and catch limits. Nevertheless, there remain many commercially important species for which fishery-independent data are not collected regularly (non-quota species). This is particularly the case for small-scale inshore fleets that are often found in rural or inaccessible areas of the coast, which reduces the accessibility for regular monitoring purposes. Both internationally and regionally, there is a need to extend the number of species for which population status data are collected if we are to implement more ecosystem-based approaches to management and meet current EU legislative commitments.

In recent years, the European Union has adopted a range of measures that mandate the provision of data which provide insights into population status across a much wider range of species than at present. The Marine Strategy Framework Directive (MSFD) was adopted in 2008 with the aim of achieving Good Environmental Status (GES) in the marine waters of the European Union by 2020. The primary objective of the MSFD is to ensure that marine biodiversity is maintained (EU, 2008). Concomitantly, the reformed Common Fisheries Policy (CFP) requires that an ecosystem-based approach to fisheries management is adopted such that marine biological resources are exploited sustainably and that the marine environment is protected to allow the achievement of GES by 2020 (EU, 2013).

The introduction of the MSFD and the reform of the CFP will require EU member states to commence collection or improve the collection of data for species which previously required little or no formal reporting on catches or catch composition. Reporting requirements of the CFP are moving towards ensuring that stocks are exploited at a level of fishing mortality that would achieve the maximum sustainable yield (MSY) (COM, 2006). In addition, the MSFD aims to "... contribute to coherence between different policies and foster the integration of environmental concerns into other policies, such as the Common Fisheries Policy (CFP)... ".

The CFP and MSFD are linked via descriptor three of GES, which states that populations of commercially exploited fish and shellfish must be within safe biological limits and exhibit an age structure and size distribution indicative of a healthy stock. This descriptor will apply not only to the quota species that are reported upon already by member states but also to other locally important species. The list of species is expected to include those species that regionally make up >90% of the landings by weight or economic importance (ICES, 2014). Under descriptor three, there are three criteria for assessing GES. For criterion one, it is expected that member states will provide an estimate of fishing mortality as a primary indicator. If this is not possible, then the catch to biomass ratio will be permissible as an indicator of GES. The second criterion will require spawning-stock biomass to be reported or, if this is not possible, other biomass indices may be used. Finally, under criterion three, member states will need to report the proportion of fish larger than the mean size of first sexual maturation and the 95th percentile of the fish length distribution observed in research vessel surveys. For the UK (and many other EU member states), >90% of the landings or regionally economic important species will include shellfish species such as scallop, crab, lobster, and whelk (MMO, 2013) which are not currently reported on under the CFP. Therefore, the burden of data collection is set to increase dramatically, which will necessitate the consideration of innovative means to collect the data, especially given the challenges of working with small-scale inshore fleets.

Currently, most statutory fisheries data collection relies on self-reporting of landings, point of first sale data, port sampling, and on-board sampling by fisheries officers. Landings, first sale, and port sampling data provide information only on the part of the catch that is legal to land and hence miss data on undersized or other prohibited life stages which will be essential to assess MSY and hence meet descriptor three requirements. Although on-board observers or scientific vessel surveys might collect more detailed data, these approaches are time-consuming and expensive.

Given the policy drivers above, data collection needs will increase considerably in the next 5 years. This fact combined with ever more constrained budgets means that there is a need for innovative ways to collect fisheries data that are cost-effective and accurate. The use of electronic technology for enforcement (e.g. Vessel Monitoring Systems and electronic logbooks) are currently well-established practices. However, the use of technological solutions to increase the coverage and reduce the cost of fisheries data collection capacity is an emerging science initiative. Progress has been made worldwide in using electronic monitoring [e.g. Closed Circuit Television (CCTV) cameras] to monitor bycatch in several fisheries, including the shark gillnet fishery in South Australia (Lara-Lopez *et al.*, 2012), the Northern Australian Prawn Fishery (Piasente *et al.*, 2012), the Alaskan Rockfish Fishery (National Marine Fisheries Service, 2011), and the Alaskan Halibut longline fishery (National Marine Fisheries Service, 2011). Baited underwater cameras have been used to estimate abundances of fish on reefs (Willis and Babcock, 2000) and dual camera systems (two cameras positioned at known distances apart and known relative angles, also known as stereo-paired cameras) have been used to estimate fish abundance and size underwater (Costa *et al.*, 2006). Recently, a stereo-paired camera system was used to produce accurate counts and lengths of fish passing through a trawlnet extension (Rosen *et al.*, 2013). Many of these trials have realized considerable cost savings by using electronic monitoring instead of on-board observers. Therefore, the development of these technologies has a significant role in addressing the need to broaden and streamline the increasing demands for data collection. Using technology also mitigates issues surrounding self-sampling, primarily the belief that samples or reporting from fishers may be biased or not collected as rigorously as by on-board observers (Kraan *et al.*, 2013).

The present study evaluated the potential of using on-board camera systems to collect data from small-scale inshore fisheries. Specifically, we evaluated the reliability of the hardware and its ability to collect images of sufficient quality to generate data comparable in quality with that gathered by on-board observers. We focused on trap fisheries for brown crab (*Cancer pagurus*) and lobster (*Homarus gammarus*) in Wales. These fisheries are among the most valuable fisheries in the UK, but there is no formalized fishery-independent data collection at present for either species.

Landings of crabs by UK vessels have increased from 24.8 thousand tonnes in 1996 to 29.5 thousand tonnes in 2012 and were worth £38.3 million in 2012 (fourth most valuable in the UK). Over the same period, lobster landings have increased from 2.7 to 3.1 thousand tonnes and were worth £30.8 million in 2012 (seventh most valuable in the UK) (MMO, 2013). At present, the data collected for these species are inadequate to underpin the formulation of management advice to ensure their sustainable exploitation. Consequently, increased data collection and reporting will be required for both fisheries under the CFP and MSFD.

Methods

Camera system

The camera system comprised a Kodak Playsport camera and a GPS logger (GT-730 GPS data logger) that were both attached to a Newtrent iCarrier USB portable power pack (Figure 1). The camera was set to video mode at 1280 × 720p resolution at 60 frames per second. We used the maximum capacity compatible Secure Digital

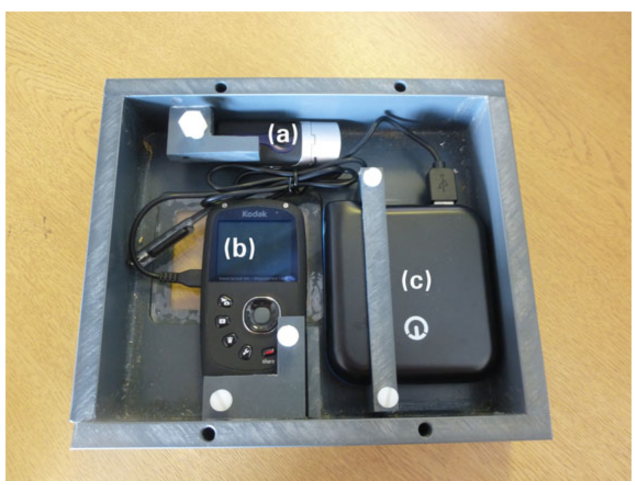

Figure 1. The prototype camera housing containing a GPS logger (a), Kodak Playsport video camera (b), and a Newtrent USB battery (c).

storage card of 32 GB, which gave ~8 h of recording time. The entire system was encased in a waterproof housing with a Perspex window against which the camera lens rested. Each system cost around £350, including the cost of electrical components and manufacture of the bespoke brackets and housings.

Camera systems were deployed on four fishing vessels, and a mobile system was used in a local crab and lobster processing factory. The sorting of catch and the layout of gear on deck varied for each fishing vessel. This necessitated that the camera position and height was vessel-specific. Always the camera was positioned directly above the catch sorting area and was mounted either to the wheelhouse, mounted to the guard rail using a custom made mount, or on a custom made platform designed to fit on top of a standard fish box (Figure 2). The exact configuration of the mounting system was finalized only after detailed discussion with each fisher. It was essential that the systems did not hinder fishers in undertaking their usual fishing activities. Mounting cameras above head height ensured that they did not present an obstruction (Figure 2a and b), although this makes the systems more difficult to operate. In one case, this was achieved by using mounting brackets to attach the mount to the wheelhouse; on another vessel, a fixture was welded to the gunwale. Systems could also easily be clamped on to the guard rail (Figure 2c) or gunwale (Figure 2d) and removed when not in use. The consultation and installations required at least two or three meetings with each fisher.

Fishers and researchers were asked to pass the catch across a defined area under the field of view (FOV) of the camera, which encompassed a reference scale. This allowed the video capture of landed, discarded, bycatch, and bait species to be identified and measured. Fishers were requested to present brown crabs ventral side up to the camera to enable sex determination. For lobsters, it was necessary for the animal to be placed dorsal side up to allow measurement of the carapace length (CL).

At-sea data collection by observers

Lobsters and crabs were measured and sexed *in situ* by observers before being passed under the camera system. This allowed direct comparison between observer and video data. It was not possible for the same researcher to collect all data; therefore, over the course of the study, five observers recorded the CL, abdomen width (AW) and sex of lobsters; and the carapace width (CW) and sex of crabs. All researchers were provided with training in how to measure the animals manually and using the videos. At the end of the study, data were tested to identify any researcher effect. Length and width measurements were taken to the nearest millimetre using Vernier callipers. Lobsters were sexed by observing the first of the sexually dimorphic pleopod pairs. Crabs were sexed by observing the abdominal flap shape and size (which is also sexually dimorphic). The measured animals were passed under the video on the platform where the reference scale was within the FOV of the camera (Figure 3). Crabs were held to display the ventral side, while lobsters were held dorsal side up. Animals were held under the camera for ~1 s or less. One second was determined to be the minimum time required for accurate visual capture and caused the least possible interference with fishing activity. The effective use of the on-board camera systems relies on the collaboration between fishers and scientists. Thus, the design of a user-friendly, low effort system that had minimal impact on fishing practices was a high priority. The system had no requirement for fishers to keep any paper records as all necessary information was automatically recorded by the camera system and GPS unit.

Video analysis

Videos were analysed using VLC media player version 2.1.3. Still images were extracted from the video footage using the VLC snapshot feature. Still images were then analysed in ImageJ version 1.47. The reference scale captured in the image was used as a reference length to estimate pixel to millimetre conversion. CL was estimated in ImageJ by drawing a straight line from the eye socket to the distal joint of the carapace for lobsters (Figure 3) and across the widest part of the carapace for the CW of crabs (Figure 3). The "measure" function in ImageJ used the reference length to estimate straight line length. The resulting length frequency data from the video was paired with the observer data (direct measurements using callipers).

Researchers sexed crabs by visual assessment of the size and shape of the abdomen. For lobsters, it was not possible to visually assess the pleopods from video footage or still images. Females have wider abdomens than males and therefore the ratio of CL to AW can be used to identify the sex of the lobsters. For this reason, we measured AW.

Statistical analysis

Sex identification

The sex determination of crabs from *in situ* observations and from the video was compared. The percentage of individuals in 10 mm size classes that were correctly assigned as either male or female from the video analysis was calculated. In all, 190 lobsters (122 females and 68 males) were measured for AW and CL *in situ* and from the videos. *In situ* measurements showed that males had an AW:CL ratio of <0.5 and females >0.5 (although juvenile female lobsters were similar to males; see Results). The AW:CL ratio was estimated from video footage. Sex was assigned using the AW:CL ratio cut-off values. The sex allocations from video footage were compared with the *in situ* allocations and the percentage that were allocated correctly was calculated for each 5 mm size class.

Size frequency

The dataset was split into two components, with data chosen at random. A training dataset using 75% of the data and a test dataset of the remaining 25% of the data were used. The relationship between the *in situ* measurements of CL (lobsters) or CW (crabs) and the CL or CW measured from the video was investigated using linear regression. Due to the height of the animals above the measuring scale, measurements taken directly from the video overestimate the size of the animals. Furthermore, other covariates influence the measurements obtained from the videos. Thus, it was necessary to apply a predictive model to correct for these errors. The size measured on the video was added as the main covariate term and researcher identity was added as a fixed effect covariate. In addition, the camera mountings differed between vessels which led to differences in the FOV of the video.

Because of the change in perspective with the distance of the camera from the subject, there was an effect on the measurements obtained from the videos. The width of the FOV was used as a proxy for the height of camera mounting as FOV can be measured from the videos. Therefore, the width of the FOV was included as a covariate in the models. Based on initial data exploration, the main relationship was found to approach an asymptote; therefore, a quadratic term for video CL or CW was also included as a covariate in the starting model. The models were fitted using R version i386 3.0.2 (R Core Team, 2013). Model selection started with the full model and employed backwards selection, dropping any

Figure 2. Examples of camera mount systems for different fishing vessels. (a) A custom mount attached to the vessel's gunwale; (b) a custom wheelhouse attachment; (c) guard rail attachment; and (d) portable system attached to the gunwale.

non-significant terms from the model and comparing AIC values between models. A model with an AIC value that was more than two points lower than a comparable model was preferred. When the AIC value was less than two points different, the simpler model was preferred. A Gaussian distribution was used for the error terms as the data were continuous.

The preferred model was then checked for assumptions and model fit. Heterogeneity of variance was assessed using scatterplots of

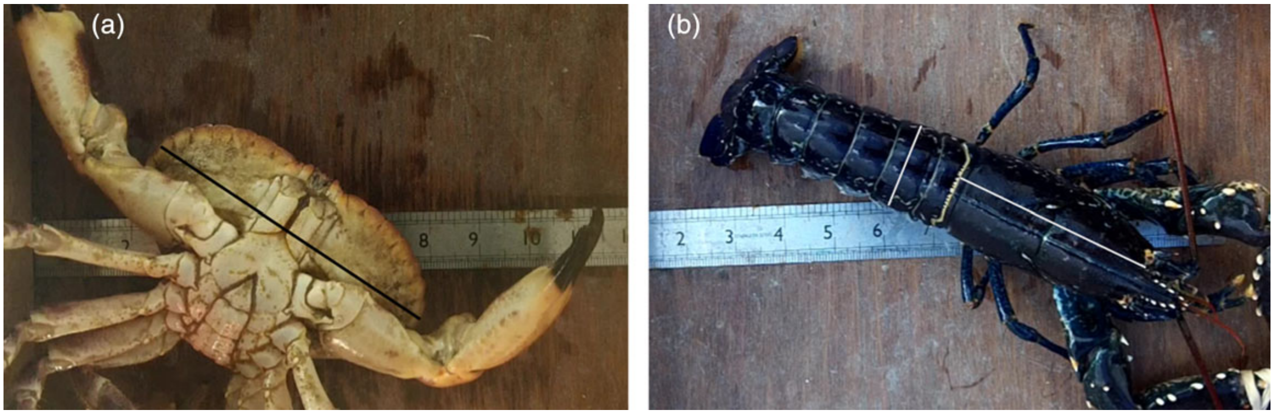

Figure 3. Two examples of images extracted from videos of animals being passed under the on-board camera. (a) Ventral view of a crab (*Cancer pagurus*) and (b) dorsal view of a lobster (*Homarus gammarus*).

standardized residuals against fitted values and all covariates. Normality was checked using Q–Q plots. Outliers were identified using leverage plots and Cook's distances. When the model assumptions were not met, generalized linear models (GLMs) with lognormal and gamma distributions were fitted using the glm function in the R base package. Model selection was carried out as described above.

Once the preferred model was found, the model fit was assessed on the second test dataset. The preferred model was applied to the test dataset using the predict function in R. The mean size, median size, size range, and number of undersized individuals were calculated for the *in situ* data and the values estimated using the video measurements and the preferred model. The size frequency histograms from the real data and predicted data were compared using the non-parametric Kolmogorov–Smirnov test. The mean and 95% confidence intervals for the difference between the real and estimated carapace measurements were estimated. Finally, 10-fold cross-validation was used on both datasets to estimate the root mean squared predictive error (RMSPE) in the R package cvTools (Alfons, 2012) and percentage error for each dataset. If the model fit is good, the predictive error will not increase when used on the second dataset and therefore the RMSPE for both datasets should be similar.

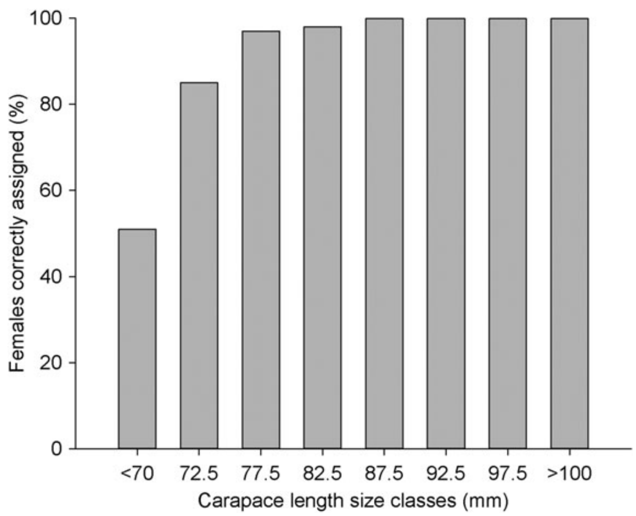

Figure 4. Percentage of female lobsters in different size classes that were correctly assigned as female using the AW to CL ratio measured from video footage.

Results

Sex identification

Sex allocation for crabs from video capture was 100% accurate. For lobsters, the results were separated into size classes, as the AW:CL morphometric relationship changes with the onset of sexual maturity. Due to small numbers of large and small lobsters, measurements were binned into 5 mm size classes except for animals <70 mm and >100 mm. All male lobsters were correctly assigned. Figure 4 shows the percentage of females in each size class that were correctly assigned as females. For lobsters >86 mm in length, the correct female sex allocation was 100% accurate. For smaller animals, accuracy of sex allocation decreased to a low of 51% in lobsters <70 mm.

Size estimation

Crab

The starting model for the relationship between crab real CW and video CW was:

$$\text{Real CW} \sim \text{Video CW} + (\text{Video CW})^2 + \text{Researcher} + \text{Field of View, where } \varepsilon_i \sim N(0, \sigma^2).$$

Using the training dataset, all terms were significant but each was dropped in turn and all models were compared using AIC values and ANOVA for model selection. The preferred model using both AIC and ANOVA included all terms. Homogeneity of variance was considered acceptable on visual inspection of scatterplots of normalized residuals against fitted values and Video CW. Boxplots of normalized residuals against the factors "Researcher" and "FOV" were also acceptable. The Q–Q plot showed that the error distribution had elongated tails and did not conform to the assumption of normality. Therefore, GLMs using the lognormal and gamma distributions were tested. Both models showed heterogeneity of variance and no improvement in the Q–Q plot and it was decided that the model using a Gaussian distribution was preferable (Table 1, Figure 5):

Table 1. The estimated parameters, *t*-values, and *p*-values for the preferred model describing the relationship between the real crab CW and that obtained from the video.

Parameters	Estimate	*t*-value	Pr(>|*t*|)
Intercept	−119.9	−4.879	<0.0001
Video CW	1.1630	14.044	<0.0001
Video CW^2	−0.0010	−3.764	0.0002
Researcher2	−0.1778	−0.216	0.8289
Researcher3	13.8900	10.87	<0.0001
Researcher4	−3.1530	−2.036	0.0422
Researcher5	11.3200	9.343	<0.0001
FOV	0.2884	4.736	<0.0001

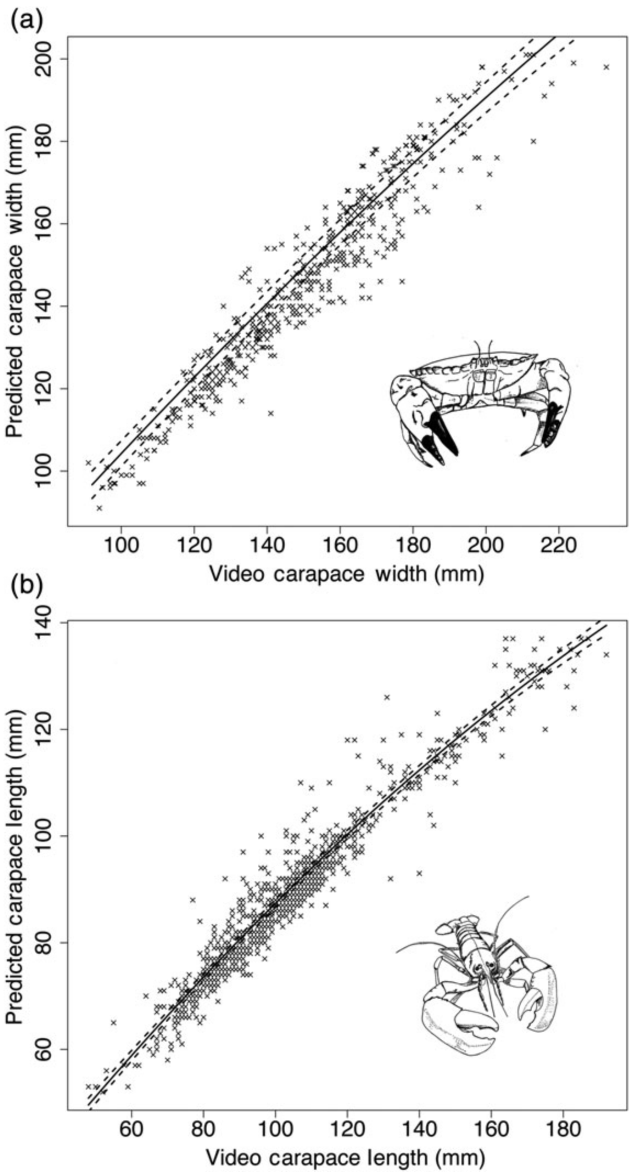

Figure 5. Modelled relationship between animal size measured from the video and those predicted by the linear models. (a) CWs of crabs and (b) CLs of lobsters. The solid line shows the fitted values and the dotted lines indicate the 95% confidence intervals.

$$\text{Real CW} \sim \text{Video CW} + (\text{Video CW})^2 + \text{Researcher} + \text{FOV, where } \varepsilon_i \sim N(0, \sigma^2)$$

$$F_{7,575} = 1496,\ p\text{−value} < 0.0001,\ \text{Adjusted } R^2 = 0.95.$$

Lobster

The starting model for the relationship between lobster real CL and video CL was:

$$\text{Real CL} \sim \text{Video CL} + (\text{Video CL})^2 + \text{Researcher} + \text{FOV, where } \varepsilon_i \sim N(0, \sigma^2).$$

When using the training dataset, all terms were significant and each was dropped in turn and all models compared using AIC values and ANOVA for model selection. The preferred model using both AIC and ANOVA included all terms. Homogeneity of variance was considered acceptable on visual inspection of scatterplots of normalized residuals against fitted values and Video CW. Boxplots of normalized residuals against the factors "Researcher" and "FOV" were also acceptable. The Q–Q plot showed that again the error distribution had elongated tails and did not conform to the assumption of normality (as for the crab data). Again GLMs using the lognormal and gamma distributions were tested and showed heterogeneity of variance and no improvement in the Q–Q plot. Therefore, it was decided that the model using a Gaussian distribution was preferable (Table 2; Figure 5):

$$\text{Real CL} \sim \text{Video CL} + (\text{Video CL})^2 + \text{Researcher} + \text{FOV, where } \varepsilon_i \sim N(0, \sigma^2)$$

$$F_{7,1063} = 2612,\ p\text{−value} < 0.0001,\ \text{Adjusted } R^2 = 0.94.$$

Testing model fit

Violating the assumption of normality can lead to poor estimation of *p*-values and can indicate poor model fit. Because we split the original dataset into two, we had a test dataset which could be used to test the model fit in addition to choosing the preferred model via AIC and checking residuals and normality.

The preferred models were applied to the video measurements in the test datasets for crab and lobster to obtain predicted sizes for each animal. Figure 6 shows the frequency histogram of the real and predicted size for crabs and lobsters. The Kolmogorov–Smirnov test

Table 2. The estimated parameters, *t*-values, and *p*-values for the preferred model describing the relationship between the real lobster CL and that obtained from the video.

Parameters	Estimate	*t*-value	Pr(>|*t*|)
Intercept	12.49107	6.895	<0.0001
Video CL	0.850957	27.27	<0.0001
Video CL^2	−0.00095	−7.244	<0.0001
Researcher2	−0.36462	−0.872	0.383
Researcher3	−1.20758	−2.867	0.004
Researcher4	−0.36908	−0.804	0.422
Researcher5	−0.14081	−0.31	0.757
FOV	−0.00198	−4.093	<0.0001

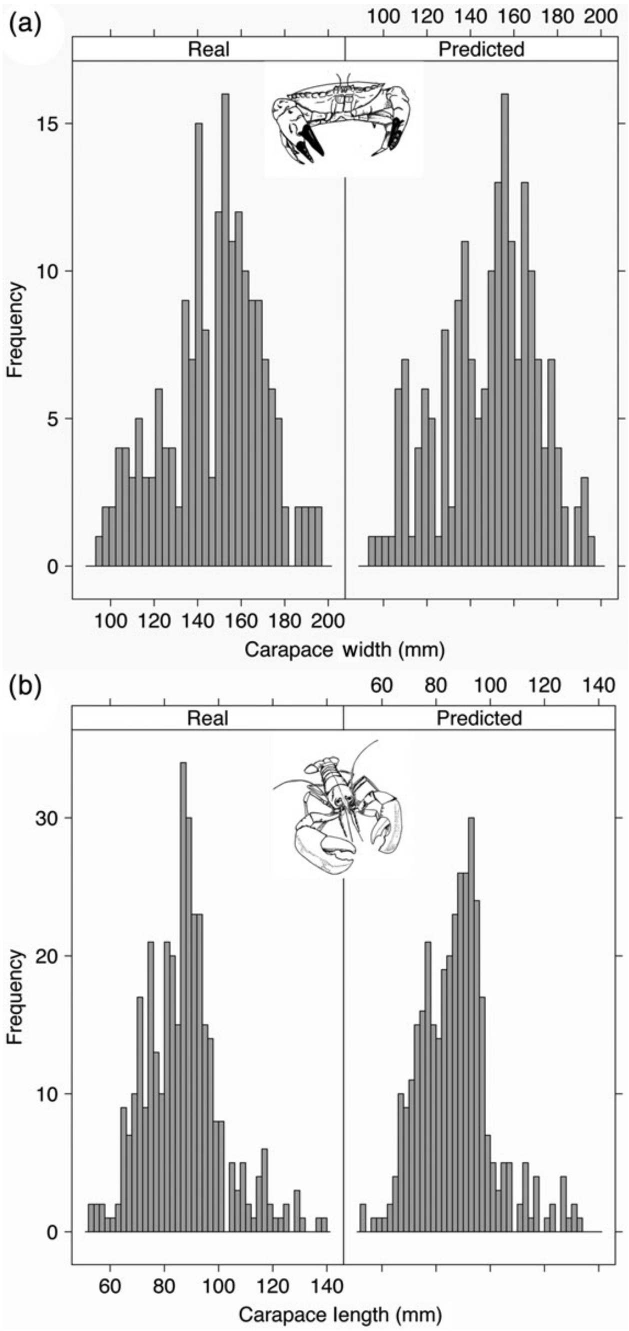

Figure 6. Frequency histograms of (a) real CWs of crabs and those predicted from video measurements (3 mm bin widths) and (b) real CLs of lobsters and those predicted from video measurements (2 mm bin widths).

showed that there was no significant difference between the two distributions (crabs: $D = 0.0521$, $p = 0.957$; lobsters: $D = 0.0451$, $p = 0.8637$). Table 3 shows the summary statistics of each size frequency distribution. Between the measured and the predicted datasets, the mean CW for crabs were identical, the median CW were 1 mm different, and the number of undersized crabs within the sample of 192 was one more in the predicted dataset. The mean and the median CL of lobsters were the same and the number of undersized (under 90 mm) within the sample of 355 was one less in the predicted dataset.

Table 3. Differences between "real" measured data and data predicted from video measurements for crabs and lobsters.

	Crabs		Lobsters	
Statistic	**Real data**	**Predicted data**	**Real data**	**Predicted data**
Mean CW/CL (mm)	148	148	87	87
Median CW/CL (mm)	151	152	87	87
CW/CL range (mm)	95 – 195	94 – 196	52 – 139	53 – 132
Number of undersized	41	42	211	210

CW, carapace width, undersized is <130 mm. CL, carapace length, undersized is <90 mm.

The mean difference between the predicted and real crab CW estimates for a sample of 192 individuals was −0.853 mm with a standard error of 0.378 mm. This gave a 95% confidence interval for the error of −1.231 mm to −0.475 mm, suggesting that the model tends to underestimate the real CW slightly. Using 10-fold cross-validation on the crab data the RMSPE on the training dataset was 2.668 mm (1.80% error for mean CW), whereas on the validation dataset it was 2.487 mm (1.68% error for mean CW). The mean difference between predicted and real data for a sample size of 355 lobsters was 0.085 mm with a standard error of 0.208 mm, which gave 95% confidence intervals of −0.322 to 0.493 mm. Using 10-fold cross-validation on the lobster data the RMSPE on the training dataset was 1.69 mm (1.90% error for mean CL), whereas on the validation dataset it was 1.63 mm (1.87% error for mean CL). The difference between the two RMSPE values for both crabs and lobsters is very small and hence supported the model fit.

Discussion

Sex identification

Sex ratios are an important biological parameter to estimate when assessing the sustainability of a commercial stock. Evolutionary theory suggests that any alteration to a 1:1 sex ratio will reduce the effective population size. The effective size rather than the census size of a population determines genetic diversity which in turn is important for the resilience of a population to stress and environmental change (Allendorf *et al.*, 2008).

Identification of sex in crabs by visual inspection of the images from the video was 100% accurate for the full size range of the 700 crabs sampled. The ability to include undersized and discarded crabs in the sex ratio calculations makes the video a more data-rich method than port sampling alone (where only the portion of the catch above the minimum landing size is recorded). Furthermore, due to the expense of sending observers to sea, on-board cameras will provide greater geographical and temporal coverage than would be possible *in situ*.

In the present study, female lobsters could be 100% correctly identified when over 86 mm in CL (and with a high degree of accuracy at 76 mm), whereas male lobsters of all size classes were correctly assigned. The AW to CL ratio becomes sexually dimorphic at maturity. Sexual dimorphism has been found in all lobsters above 80 mm and some between 75 and 80 mm (Brown, 1982). However, the ratio used to categorize sex may be regionally specific if size at maturity varies among geographically distinct locations. Nevertheless, once this ratio has been established the video method provides sex ratio data at over 95% accuracy to 11 mm below the European minimum landing size and 14 mm below the minimum landing size of 90 mm implemented in parts of the UK and Norway. With growth increments estimated at between 7 mm and 12 mm (Hepper, 1972; Shelton *et al.*, 1981; Agnalt *et al.*, 2006), it will provide sex data for the size class at least a whole moult size below the minimum landing size.

Size estimation

Size distributions of commercial catches are needed to convert landings data into size stratified abundances for length cohort analyses which is a method used to investigate MSY and yield-per-recruit. Descriptor three of the MSFD requires that "Populations of all commercially exploited fish and shellfish are within safe biological limits, exhibiting a population age and size distribution that is indicative of a healthy stock." Meeting this descriptor will require data on the size distribution of stocks, with a long-term goal of calculating MSY or similar indices to link in with the CFP. By improving temporal and spatial coverage, and providing data on undersized animals, on-board video systems can help meet the data requirements of the CFP and MSFD.

The multiple linear regression model explained 95% of the variance in the measured vs. video CWs for crabs and 94% for CLs in lobsters. However, the model violated the assumption of normality of the residuals. Lognormal and gamma distributions created strong patterns in the residuals violating the assumption of homogeneity of variance. Therefore, the preferred model used a Gaussian distribution. Violating the assumption of normality can inflate *p*-values and increase Type I errors as the true mean can be found to lie outside the 95% confidence intervals (Lumley *et al.*, 2002) but ordinary least-squares regression is generally robust to non-normality with large sample sizes. Even with extremely skewed data with a one-sided tail, linear regressions with sample sizes of more than 500 were found to be robust to deviations from normality (Lumley *et al.*, 2002). However, when predicting using a linear model, it is thought that violation of the normality assumption may be more problematic. Therefore, we decided to use a training dataset and a separate test dataset to assess the fit of the model and its ability to predict carapace sizes. The tiny changes in the RMSPE after cross-validation between the training and test dataset along with the very similar summary statistics gives confidence that the linear model can be used to predict carapace sizes from video data. The size frequency distributions between "real" *in situ* measured crab and lobster sizes and those predicted from the video images were statistically similar, indicating that video-derived data can be used in fisheries monitoring. The error associated with the size measurements from the video suggests that crabs could be binned into 3 mm size classes and lobsters into 2 mm size classes. This level of accuracy is sufficient to monitor changes in size distributions across a fishery both temporally and spatially and to address some of the increased data burden under MSFD and CFP reforms.

Several factors associated with the method could be improved to increase the robustness and reliability of the data. In our study, it was necessary to use researchers with different levels of experience that varied from relatively little experience (first experience of collecting data at sea) through to highly experienced (greater than 5 years of research experience at sea). A set protocol was explained to each researcher for at sea measuring and image analysis but the statistical model included a significant researcher term, suggesting that all researchers undertaking the image analysis will need to collect data to validate their own linear model. To be able to develop a model where there is no significant researcher term, it may be necessary to increase the level of training offered. Chang *et al.* (2010) found that length estimations from photographs of albacore (*Thunnus alalunga*) could be improved by at least 25% after additional training (the exchange of experiences and methods between the photo analysts). In lobsters, identification of the back of the eye socket can be difficult from the video images and increased training to ensure a uniform approach could decrease the researcher effect. Alternatively, increased image resolution may allow for more accurate identification of the back of the eye socket. In crabs, the widest point of the carapace is easily identifiable when the crab has its legs extended; however, if their legs are curled under the abdomen, the edge of the carapace can be obscured and so a level of subjectivity is introduced in identifying the carapace edge. Increased training could help to ensure researchers are more accurate at identifying the edge of the carapace in this situation. In addition, artificial intelligence and computer learning could be employed to detect the shape of the crab carapace and automated CW measurement could then be employed to reduce this error and remove the researcher effect.

It is important to note that the relationship between measurements taken manually and those taken from video footage will vary depending on the camera used and the height of the camera above the measuring scale. Rycroft *et al.* (2013) used measuring blocks mounted at different heights to prevent the error introduced due to the height of the animal above the measuring board. However, this error can also be accounted for in the calibration model. Therefore, using a single measuring board is sufficient.

Different camera lenses will introduce different levels of image distortion meaning that calibration is required for individual camera systems before use. Lenses introducing the least distortion are preferable to ensure the most consistent results but this needs to be balanced against financial cost. The maximum height at which a camera can be mounted depends largely on the resolution of the camera used. To accurately identify features of the animals, such as the back of the eye socket, mounting the camera closer to the subject is preferable. By incorporating FOV into the calibration model, it was possible to correct for the effects of different camera mounting heights.

Cost implications

The time taken to analyse a day's fishing from the video data depended on the catch per pot, which in turn varied seasonally with water temperature. Once the still images had been extracted it took $\sim$ 5–10 s to measure and sex the animal in each image. These data are immediately entered into an electronic form. While on-board measurements take a similar amount of time, they are usually hand written first and then entered electronically once back at the office. In addition, images can be analysed by a single person, while it is usual to send two people to sea for safety reasons. Currently, the most time-consuming aspect of the video analysis is manually extracting still images from the video. However, work is already planned to automate this part of the data processing. Once this has been achieved, the data collected from the video will not only be highly accurate, and more detailed than port sampling, but also much more cost efficient than at-sea sampling, which also has to take into account the travel time to sampling locations. Chang *et al.* (2010) compared the cost of on board observing, port sampling and photo analysis for the Taiwanese albacore longline fishery and found that for 100 USD you could sample either 10 fish at port, 35 fish on board or138 fish by photo analysis. Automated image processing would further increase the time and cost savings.

Wider application and future development

Automatic image extraction was achieved by Zion *et al.* (2000, 2007) using a video camera and computer which automatically grabbed images of fish only if they swam past the camera in the correct orientation. This image shape analysis was based on moment-invariants and could be applied to the systems used in the present study. It is also possible that computer learning could be used to automatically measure the crabs' CWs. More research is needed to achieve this and to investigate the possibility of automated CL measurements of lobsters.

The systems used in this study were very simple and inexpensive to install. However, they did require fishers to activate the camera from within the protective housing and to recharge the battery pack at intervals. It is possible to incorporate an external power button or to activate the system through automatic sensors (e.g. Daum, 2005). The systems could also be connected to vessels' power supplies. While such modifications will increase the ease of use, they will also add to the installation costs. One important development, however, would be the integration of position data with images.

Vessel Monitoring Systems (VMS) are used widely in fisheries science. VMS data can be used to map fishing activity (Gerritsen and Lordan, 2011; Jennings and Lee, 2012) and quantify fishing impacts (Witt and Godley, 2007; Hinz *et al.*, 2009; Lambert *et al.*, 2012). Positional data can also be combined with logbook data (Deng *et al.*, 2005; Bastardie *et al.*, 2010) to examine catch per unit effort (ICES, 2011; Murray *et al.*, 2011) and to estimate biomass indices (Murray *et al.*, 2013). Incorporating on-board cameras with VMS and logbooks would provide spatially referenced data on catch composition and discards that could be used in stock assessments, potentially obviating the need for fishery-independent data.

The use of camera systems could also be preferable to on-board observers based solely on data quality. There is evidence that on-board observing can be biased and not representative of normal fishing practices. Faunce and Barbeaux (2011) found evidence of an observer effect (changes in fishing practices due to the presence of observers) and a deployment effect (non-random distribution of observers) with on-board observing of the North Pacific Groundfish Observer Programme when comparing vessel landings from trips with and without observers. Benoît and Allard (2009) also found evidence for observer and deployment effect in the Gulf of St Lawrence fisheries. Using technology can possibly eliminate these effects, or at least reduce the deployment effect. A deployment effect would still be possible because only boats with camera systems could be used. However, deploying camera systems on a larger selection of boats could reduce this problem. In addition, Kraan *et al.* (2013) identified that on-board sampling tends to result in clustered samples and small sample sizes. The use of on-board cameras can help to mitigate these problems, providing greater spatial and temporal coverage.

The presence of the cameras could also influence fisher behaviour. The systems described in this study require collaboration with fishers; they are not a fisheries enforcement tool. Ensuring that landed animals are not below the minimum landing size, for instance, is best achieved through at-sea or shore based monitoring. The cameras can be activated whenever fishers choose. When activated they show what has been caught in each pot and, importantly, they provide a sample of all animals caught not just those landed. While it takes only a few seconds to pass each animal beneath the camera, over the course of a day's fishing this could slow fishing operations noticeably. Therefore, it is expected that fishers would use the camera systems on a limited number of hauls on certain days. Integration of GPS with videos would increase certainty over the exact sampling time and locations but at greater cost for each system.

While this study has focused on brown crabs and lobsters, there is no reason on-board camera systems cannot be used to record size and abundance data on other species, including bycatch species. Electronic Monitoring systems including CCTV have been trialled in multispecies longline fisheries over several years as a tool for addressing catch monitoring inadequacies (Ames, 2005; Ames *et al.*, 2007) including incidental catches of seabirds (Ames *et al.*, 2005). CCTV has also been trialled in the Irish Sea *Nephrops norvegicus* fishery to monitor cod bycatch (Pasco *et al.*, 2009). More recently, Rycroft *et al.* (2013) used cameras not as an alternative to observers, but as a way for researchers to measure more animals in the field.

The potential application of the systems used in this study extends beyond the recording of size and sex. Cadrin and Friedland (1999) identified the potential to identify different stocks using image analysis of morphometrics. More recently, Rycroft *et al.* (2013) were able to discriminate different *Homarus americanus* stocks using analysis of morphometrics captured from videos. Using video also has the benefit of providing a data archive that can be reanalysed if necessary, as was highlighted by Rycroft *et al.* (2013).

Ames (2005) recognized insufficient frame rates (leading to blurred images) and excess video compression as limitations to using cameras as bycatch monitoring tools but these problems were later overcome (Ames *et al.*, 2007). Furthermore, video camera technology has progressed greatly in recent years, allowing high frame rates (60–120 frames per second) and high resolutions (1280×720 or more) to be recorded. Ongoing improvements in video technology, combined with reduced costs, will only increase the applications of on-board camera systems to fisheries monitoring.

In conclusion, camera systems were found to be a suitable method for collecting data on the size and sex of crabs and lobsters. The error attributable to using video data rather than manual measurement was less than 3 mm, which is sufficient to detect growth in *C. pagurus* and *H. gammarus*. The method also allowed the sex of crabs and lobsters to be detected for most sizes. The requirements to collect basic species data are increasing and the ability to do so without on-board observers will reduce the cost implications of these new requirements. Using camera systems to collect data is also likely to improve temporal and spatial coverage relative to using on-board observers, as well as providing the benefit of a video archive. Automation of image extraction and, potentially, measurements will increase the application of video systems for data collection in a wide range of fisheries.

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