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Image based estimation of oat panicle development using local patterns

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May 24, 2014

Abstract

Flowering time varies between and within species, profoundly influencing reproductive fitness in wild plants and productivity in crop plants. The time of flowering, therefore, is an important statistic that is regularly collected as part of breeding programs and phenotyping experiments to facilitate comparison of genotypes and treatments. Its automatic detection would be highly desirable.

We present significant progress on an approach to this problem in oats, an under-developed cereal crop of increasing importance. Making use of the many thousands of images of oat plants we have available, spanning different genotypes and treatments, we observe that during flowering, panicles (the flowering structures) betray particular intensity patterns that give an identifiable texture that is distinctive and discriminatory with respect to the main plant body and can be used to determine the time of flowering. This texture can be located by a filter, trained as a form of a ‘Local Pattern’. This training phase identifies the best parameters of such a filter, which usefully discovers the scale of the panicle spikelets.

Results are presented that demonstrate the success of the filter. We proceed to suggest and evaluate an approach to using it as a Growth Stage detector. Preliminary results show very good correspondence with hand-measured ground truth, and are amenable to improvement in a number of ways. Future work will build on this initial success and will go on to locate fully mature panicles, which have a different appearance, and assess whether this approach can be extended to a broader range of plants.

1 Introduction

Cereal (and other plant) development goes through a number of well defined stages that are used globally to perform monitoring and comparison (BBC 2001, Zadoks et al. 1974). Thus, for example, the widely used Zadoks scale defines Growth Stage (GS) 0 as dry seed, GS 20 appearance of the first tiller, GS 50 appearance of first spikelets of the panicle, and so on. Catalogues – or atlases – of these stages are accompanied by representative drawings or images. This atlas-based approach to documenting development is familiar in many domains, in particular medical imaging where ‘expert’ judgements are recorded to assist classification of individual cases. These atlases often prove useful tools when automatic imaging techniques are later introduced to the domain (e-A 2014). Just one example, wrist radiography, is illustrated in (Gertych et al. 2007, Tanner & Whitehouse 1975).

Worldwide, there is increasing interest in applying imaging technologies to plant phenotyping (Furbank & Tester 2011), and a growing number of installations able to perform large scale phenotyping experiments – (APP 2014, JPP 2014, NPP 2014) are just some examples. Usually, these are based on automated greenhouses that can administer pre-programmed treatments to a number of plants, of which they likewise make regular automated measurements. These installations permit large scale experiments to be conducted over time within complex regimes, with minimal staff input. Much can be gained from the simplest of monitoring such as a photograph, but a variety of other image modalities (UV, IR, NIR, structured light), and root analysis, are also available. Measurements of benefit to biologists can then fall into a number of categories:

1. Replication/mimicry of ‘simple’ measurements performed manually. These include plant height and projected area (which can be used to approximate mass).
2. Replication/mimicry of less easily accessible measurement, for example, atlas growth stages.
3. Measurements that may be of benefit that have not been made systematically in the past.

The science of computer vision also continues to exhibit significant progress. In particular, many algorithms are now in every day use that operate on a ‘train then classify’ approach, where some form of automatic detector is built from knowledge of a (perhaps very large) number of training cases (Šonka et al. 2014). Such detectors have in recent years become increasingly sophisticated. High throughput phenotyping installations represent very fertile territory for many such algorithms, and coupled with good quality domain atlases, we might hope to build automatic systems that replicate significant parts of the work currently done very labour-intensively. More interestingly, we might seek to develop measurements accessible to computer extraction that would be difficult or costly if collected manually. Such activity has been growing in popularity in recent years, for example (Campillo et al. 2010, Hartmann et al. 2011, Reis et al. 2012, Sirault et al. 2013, Song et al. 2014).

In this paper we present work in progress on one such example: flowering in oats. This is an important property for commercial reasons, since it impacts on adapting varieties for particular agronomic purposes. However, the spikelets of the panicle are small and easily

67 obscured by the body of the plant making their reliable detection in images a challenge –
68 we are unaware of attempts to solve this problem using computer vision, although studies of
69 images of pre-isolated panicles have been conducted (Al-Tam et al. 2013, Huang et al. 2013).
70 We find that areas of the image in which spikelets are emergent betray textural properties
71 that are amenable to image-based extraction, and we show how this property can be used
72 to estimate critical growth stages – we consider this work to be in the second category
73 enumerated above. This work can be used as the basis of subsequent filters which will
74 identify later growth stages of interest, such as full flowering. It may also be possible to
75 generalise the approach to related cereals such as rice and millet.



(a) An oat plant – the plant is approximately at GS 60 (Zadoks et al. 1974).



(b) Close up of a panicle.

Figure 1: Images captured at the UK National Plant Phenomics Centre (see Figure 3); image quality is distinctly sub-optimal as the system was still in commissioning.

76 2 Background

77 2.1 Flowering time in oats

78 The oat plant in development goes through a number of well understood and documented
79 phases (BBC 2001, Zadoks et al. 1974); one of particular interest is progress in flowering:
80 phase GS 50 represents the appearance of the first spikelet (of the primary tiller), GS 60
81 would be full heading but not flowering, and GS 70 full flowering. This is straightforwardly
82 observable in visual inspection of growing plants, within tolerable error limits. It is possible
83 and normal for a plant to occupy more than one stage at any given time as successive tillers
84 develop. Figures 1 and 8 gives some illustration.

85 Flowering is a major developmental transition in the life history of plants and has a major
86 impact on grain yield in cereals such as oats. Control of flowering time is essential to maximise
87 reproductive success, enabling completion of seed development in favourable environmental
88 conditions. This adaptive effect has been exploited in agriculture to ensure that plants flower
89 synchronously and at the optimal time to maximise seed yields (F & G 2012). Optimum
90 floral initiation and development ensures the maximum use of resources available throughout
91 the growing season, and minimises the exposure of sensitive floral tissue to biotic and abiotic
92 stress (Worland 1996). In temperate environments with a long growing season, late flowering
93 ensures a long vegetative phase for maximal resource capture leading to high grain yield

94 potential. Early flowering is important for environments where the effective growing season
95 is short either due to extremes of temperature or water availability or where multiple cropping
96 seasons within a year are possible (Locatelli et al. 2006). Considerable genetic variation exists
97 for the control of flowering time and plant breeders continue to select for optimal flowering
98 time to maximise yield for specific environments. The ability to quickly and accurately
99 measure flowering time is important to characterise the genetic variation that exists for
100 this trait and to determine the influence of the environment on the its regulation. This
101 information can be combined with genetic analysis (Tinker et al. 2009) to identify regions
102 of the genome controlling flowering time (Holland et al. 2002, Locatelli et al. 2006, Locatelli
103 et al. 2008, Nava et al. 2012) Knowledge of both flowering time and the genes regulating it
104 can then be used to precisely manipulate this trait within a plant breeding programme.

105 2.2 Classification from Binary and Ternary patterns

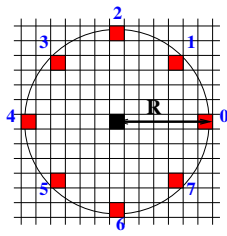
106 Texture characterisation is a well established branch of image processing and vision. It is
107 very common for texture rather than shape or intensity to be the most accessible feature
108 of certain image regions; it may be clear that this is frequently the case with images of
109 plants. The range of well-established techniques is very wide (see, for example, (Šonka
110 et al. 2014)). Recently, *Local Binary Patterns* (LBP) have found especial favour in this
111 area (Ojala et al. 2002), demonstrating tolerance to a number of commonly encountered
112 imaging problems while being appealingly simple. Since we determine (see Section 3) that
113 panicles in development exhibit characteristic binary (in fact, red/green) patterns, we choose
114 to experiment with these.

115 A LBP is derived at every pixel of an image; centred at the pixel, a circle quantised into q
116 pixels is drawn at some radius R , and the pixels so defined thresholded by the intensity of
117 the central pixel – thus a q -bit pattern is defined at each pixel. Figure 2a illustrates this
118 for $q = 8, R = 6$ – a bit is determined at each red pixel according to whether it exceeds the
119 central one or not, and a q -bit number is assembled in the order indicated, and associated
120 with the black pixel. This representation very efficiently captures local contrast patterns.

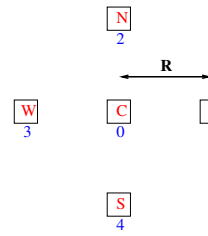
121 Now square windows of dimension W are considered, and a histogram of the responses within
122 constructed. This histogram has W^2 responses in the range $[0, \dots, 2^q - 1]$, and the vector
123 it represents can be a very powerful texture descriptor; other areas of the image generating
124 similar histograms will have similar texture. Such a histogram can be calculated at each
125 pixel position by sliding the window through the image; this could become very costly for
126 large images and it is often sufficient to tile the image with $W \times W$ windows, or perhaps
127 compromise by sliding the window by $\frac{W}{2}$ pixels rather than 1.

128 LBPs lend themselves to very efficient implementation, and tuning to exploit the occurrence
129 of areas of uniform intensity. It is further straightforward to adapt the idea to cope with
130 reflective symmetries or to impose rotational invariance.

131 A companion approach would be to define a binarisation of the original image (at simplest,
132 by thresholding), and derive per-pixel responses in a similar manner. Hereunder we describe
133 a reduction of the image to three intensities, and a consequent ternary pattern to characterise
134 local texture.



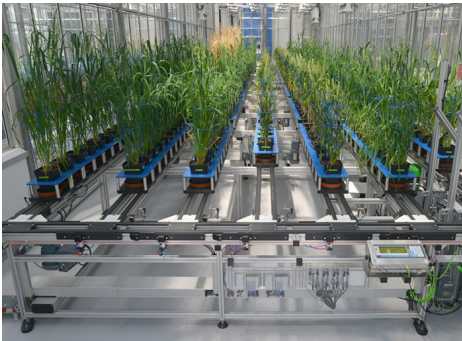
(a) Local Binary Patterns – a quantised circle around a central pixel is considered. Quantisation and radius are filter parameters.



(b) **The local pixel pattern used in this application** – a central pixel has four neighbours defined at distance R .

Figure 2: Texture description by local patterns.

135 2.3 Imaging environment



(a) One of the robotic greenhouses.



(b) Plants (here, maize) entering the imaging chambers.

Figure 3: The UK NPPC.

136 The UK National Phenomics Centre (NPPC) has recently been established at the university
 137 of Aberystwyth and exists to conduct large scale phenomics experiments. The full facility is
 138 described elsewhere (NPP 2014); it affords a variety of imaging modalities and opportunities
 139 for controlled environments and treatments. Here, it is sufficient to appreciate that up to
 140 850 plants can be imaged daily under specified conditions. Imaging can include rotated and
 141 birds-eye view pictures of each plant.

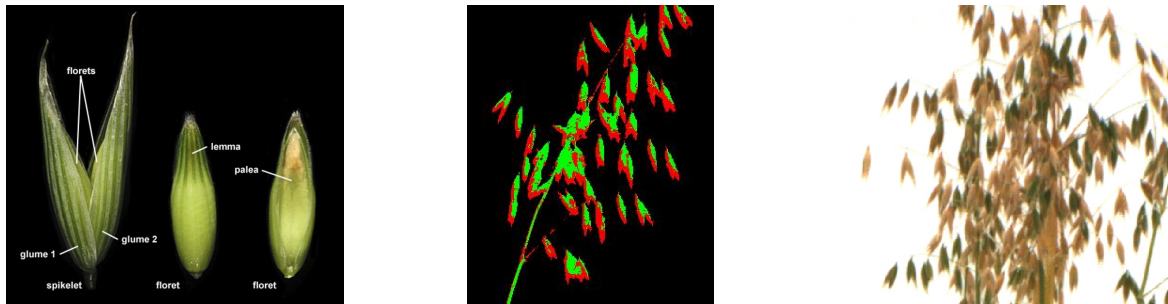
142 3 Detecting panicle emergence in images of oats

143 An experiment was conducted over a ten week period on a mapping population derived
 144 from the Buffalo and Tardis varieties. 3 individuals of each line and some parental controls
 145 provided 282 different plants, which generated a total of over 9700 RGB images¹: The plants

¹Aspects of the system were being commissioned during this experiment. In normal circumstances many more images of higher quality and greater consistency, and other image modalities, would have been generated during this period.

146 develop from a single tiller through flowering to fully senesced, and we are interested in
147 panicle development, particularly on the primary tiller.

148 Individual spikelets are small features, many of which are often occluded or obscured by
149 other plant matter, meaning that attempts to locate or count them explicitly will be very
150 challenging. On the other hand, to recognise the onset of flowering it would be sufficient to
151 recognise an image area in which spikelets probably lie. Close inspection reveals that the rim
152 of a visible spikelet has a narrow yellow band even during very early stages of development,
153 implying that the red channel will be dominant in that band in an RGB representation.
154 This is almost certainly due to the material of the glume being very different to the lemma
it encloses. Figure 4 illustrates this effect.



(a) Structure and terminology of oat spikelets.

(b) Fig. 1b partitioned as background, red-dominant, green-dominant.

(c) Later in development, spikelets become predominantly yellow.

Figure 4: Panicles and spikelets (Image 4a: Anna Gardner, with permission from Iowa State University).

155
156 Segmentation of the plant tissue and suppression of the (blue) support frame is straight-
157 forward in the controlled imaging environment and is performed routinely on all images we
158 collect. Thereafter we could simply seek dominance in the Red or Green channels; in fact,
159 our approach is slightly more sophisticated. A (large) representative subset of plant matter
160 pixels over the entire time series of images is considered: The RGB triples are 24 bit, but
161 this very large data space is subjected to K-means clustering (Šonka et al. 2014) to facil-
162 itate various procedures independent of this application (such as detection of senescence).
163 Empirically we have discovered that for all image sequences we have inspected, 25 clusters
164 provide an adequate representation (that is, significantly increasing the number of clusters
165 reduces information loss in the quantisation only marginally, while using 20 or fewer begins
166 to increase this loss appreciably). No qualitative difference in results has been observed by
167 changing the K-means initialisation, and this was done randomly.

168 We quantise the plant pixels using this approach, and then partition the cluster exemplars as
169 either red or green dominant (it is no surprise that none are blue-dominant), which allows us
170 to partition the image as black (for background), red and green – this approach encourages
171 the small spikelet regions to emerge robustly and to reduce noise effects. The fine scale
172 pattern evident in Figure 4b is rarely if ever evident in other areas of the image, where
173 green and red regions are usually larger, and rarely in the geometric arrangement seen in
174 the spikelets.

This leads us to suggest a texture detector that would highlight such regions: we experiment

with a very simple form illustrated in Figure 2b, considering a central pixel and its four orthogonal (E/N/W/S) neighbours at a distance of R . Arbitrarily labelling black as 0, green as 1 and red as 2, the per pixel texture is defined as

$$C + 3E + 9N + 27W + 81S$$

175 giving a value in the range $[0, 243]$. Then a histogram computed over some window would
 176 deliver a 243-dimensional feature. We can ameliorate this size by

- 177 • Neglecting responses of constant (all background, red or green) response, since the
 178 panicle is characterised mainly by the proximity of variable response. This reduces
 179 dimensionality to 240.
- 180 • Perhaps imposing a vertical symmetry constraint. The spikelets hang to left or right
 181 but we do not mind which; in each case they have a green apex and a red lower rim. If
 182 we consider the EW pixels of Figure 2b, and let them be *unordered* (so, for example,
 183 Black/Red and Red/Black are taken as the same), the detector will become slightly less
 184 specific, but the dimensionality reduces to 159. (Since there are many pattern instances
 185 in which E and W pixels are the same this does not halve the dimensionality).

186 Accordingly, we have experimented with 240 and 159 dimensional detectors.

The approach is to define a square window of size W and radius R , and determines the frequency histogram in panicle areas of **ground-truthed** images. Unclassified images are then presented, marked as $(background, red, green)$ and a histogram computed at each pixel, which is then compared with the learned model. Histograms are compared using the Hellinger distance (Hellinger 1909): **Choice of this metric was somewhat arbitrary, but it seems improbable that any alternative would significantly affect results.** If \mathbf{h}^1 and \mathbf{h}^2 are two normalised histograms, this distance is

$$H(\mathbf{h}^1, \mathbf{h}^2) = \sqrt{1 - BC(\mathbf{h}^1, \mathbf{h}^2)}$$

where BC is the Bhattacharyya coefficient

$$BC(\mathbf{h}^1, \mathbf{h}^2) = \sum_i \sqrt{h_i^1 \cdot h_i^2}$$

187 where i counts through the components of the vectors $h_i^{\{1,2\}}$. This distance is then in the
 188 interval $[0, 1]$, and lower numbers will be indicative of spikelet presence.

189 In summary, we develop a panicle indicator by performing:

190 **Algorithm:** Determine panicle-like response in an image

- 191 1. Choose R and W .
- 192 2. For a small number of images, outline areas that contain panicles, or parts thereof.
 193 (This does not need to be done with great precision, making it a quick operation).
- 194 3. Convert the images to be 3-level, black, red, green. Select pixels randomly from the
 195 panicle areas and compute a 159-wide histogram with the given R, W .

- 196 4. Total the histograms and normalise, providing a 159-wide probability distribution \mathbf{p}
 197 that describes panicle areas.
- 198 5. For an unexamined image, compute a histogram at each pixel and normalise it. Record
 199 the Bhattacharyya distance between the observation and \mathbf{p} as the measure of panicle
 200 evidence at that pixel.

201 The choice of R and W at step 1 should be guided by the performance of the resulting filter
 202 – a systematic optimisation of this choice is discussed in section 4.1.

203 Step 5 here could be time-consuming and could be performed in a subset of pixels defined
 204 by a tessellated tiling, or some overlapping tiling of the image. In our experiments we have
 205 used a $W \times W$ window slid by quanta of $\frac{W}{2}$. In Section 4.2 we describe how this response
 206 filter may be used in a series of images to estimate day of onset of flowering.

207 4 Results

208 4.1 Choice of filter parameters

209 Five images with panicles at GS 50-60 were marked by hand, giving masks indicating posi-
 210 tive/negative regions. Training was performed on pixels selected randomly from these posi-
 211 tive masks, and the resulting histogram frequencies were then tested on marked image areas
 212 not used in training. For the sake of efficiency in testing, histograms were not computed
 213 at every pixel, but rather in square windows of size half that over which the histogram was
 214 computed.

Performance was measured by computing a Precision-Recall (PR) curve over the test-set, and
 for a given R, W pair recording the area under the curve. PR is often used in preference to
 ROC curves when there is a significant (order of magnitude) difference between the number
 of positives and negatives in a dataset, as here. In the normal manner, we define for a given
 threshold of the filter output

$$TP = \text{True Positives} , \quad FP = \text{False Positives}$$

and TN, FN similarly for negatives, then

$$P = \frac{TP}{TP + FP} , \quad R = \frac{TP}{TP + FN}$$

215 P and R are then plotted against one another - for a perfect classifier, the area under this
 216 curve is 1, while a random classifier will give area 0.5.

217 In all such experiments, the 159-dimensional feature performed very slightly but consistently
 218 better than the 240-dimensional one, and we settle on using it accordingly. There was no
 219 foreknowledge of ‘good’ values for R and W , and ranges of $R = 1, \dots 12, W = 5, 10, 15 \dots 120$
 220 were selected arbitrarily.

221 Figure 5 illustrates performance: increasing brightness corresponds to better performance.
 222 As R increases beyond 2 overall performance deteriorates, with a best response at $R =$

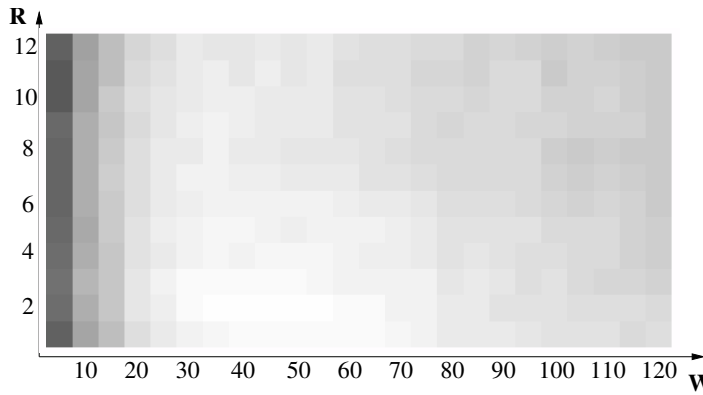


Figure 5: Areas under PR curves for various values of R and window sizes W , where light is high and dark is low (scaled for display). The best (brightest) response is seen at $R = 2, W = 45$.

223 $2, W = 45$ where the area is 0.74 (the worst response is at $R = 9, W = 5$). These figures are
 224 reasonable at the scale of image we have collected: Figure 6 shows two 45×45 windows of
 225 spikelets – it is clear that the best-performing detector has discovered the approximate scale
 226 of the feature of interest. At the right of the figure, a 10×10 window of a detail from one of
 227 the spikelets illustrates that $R = 2$, implying a 5×5 window around the central pixel, will
 capture the local red/green/black variation that characterises a panicle.

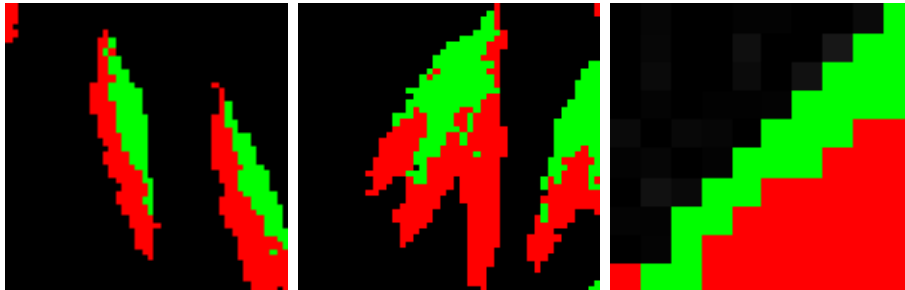


Figure 6: Close-ups of parts of a panicle: left and middle, 45×45 windows, right, a 10×10 window.

228
 229 As further confirmation that the detector is functioning as it should, Table 1 shows the
 230 ternary patterns that dominate the trained histogram. Ten of the 159 dimensions provide
 231 over 50% of the response, and the patterns capture the co-occurrence of background, red
 232 and green as expected. In particular, the fifth, seventh, eighth and ninth patterns illustrate
 233 that boundaries at the ‘top’ of regions are predominantly green, and at the ‘bottom’ red.

234 4.2 Derivation of GS estimator

235 We have used the output of the imaging system to exercise this ($R = 2, W = 45$) ternary
 236 filter on image sequences of 82 developing plants. **The filter provides strength of belief in
 237 the existence of a panicle – Figure 7 illustrates thresholding selection of this measure, colour
 238 coding the True/False Positives and Negatives.** It is clear that the central image provides

	0.105		0.039
	0.082		0.038
	0.069		0.034
	0.059		0.034
	0.041		0.029

Table 1: The ternary patterns that the filter predominantly seeks, with their histogram frequencies — these 10 (of 159) contribute over 50% of the observation in ‘good’ areas. (Black is background, green and red denote dominance of plant pixels in the green and red channels Note that the EW pixels are considered to be *unordered*.)

239 the best indicator. This image also highlights the opportunity to restrict inspection to the top of the plant, having an immediate beneficial effect on the False Positive rate.

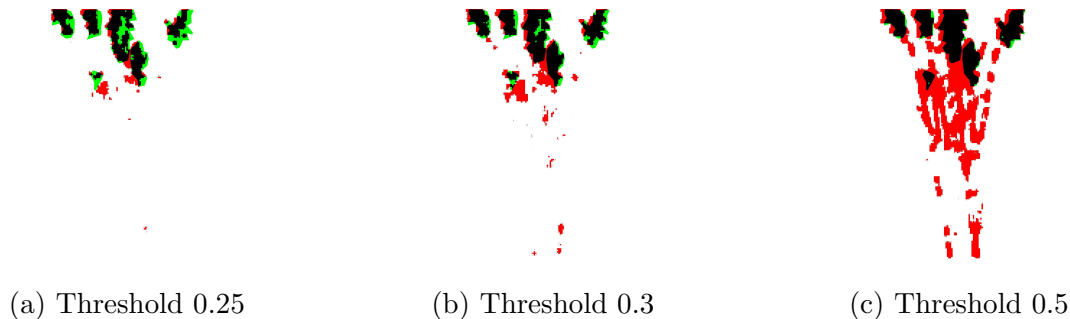


Figure 7: Thresholding the panicle filter: White pixels are True Negatives, black are True Positives, green are False Negatives and red are False Positives.

240
241 Figure 8 shows the development of a single plant over a 90 day period². This confirms that we
242 can probably neglect any response that is, say, below half plant height. More interestingly, it
243 is possible to verify that all panicles produce a response of some kind, but the very strongest
244 (red) responses are evidenced well into development.

245 It remains to indicate how this detector may automate the *estimated* measurement of GS.
246 Figure 9a shows for the plant of Figure 8 the number of pixels within certain Hellinger
247 thresholds (the colours corresponding to that Figure).

248 The precise patterns of these response curves are not easy to model – as the first tiller
249 begins to senesce and the second and subsequent panicles begin to develop, we will expect
250 a very noisy superposition of peaks and troughs. Nevertheless, the early phases of each
251 response curve may be expected to be approximately zero, prior to the panicle emergence,
252 followed by a sharp climb corresponding to the primary tiller’s panicle which, while probably

²The day of sowing precedes day 1 of observation by some time – plants are not introduced to the imaging system before they are visible, at GS 20 or later

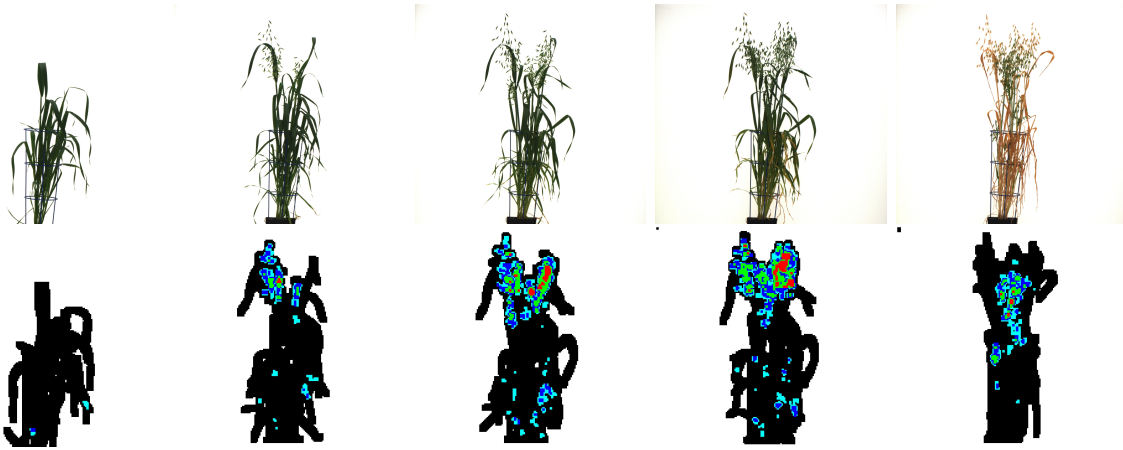


Figure 8: Development of a particular plant seen through the panicle detection filter. This plant was imaged over 90 days, day 1 being April 20th 2013, which was 31 days after sowing: these images were recorded on days 36, 51, 56, 67, 85. Best estimate GS for the primary tiller are 39, 59, 65, 73, 85. Filter response (weight of evidence) is coded as black (low), light blue ($H < 0.4$), dark blue ($H < 0.35$), green ($H < 0.3$), red (high) ($H < 0.25$).

253 quasi-sigmoidal, may be approximated as linear. Piecewise linear approximation to noisy
 254 observations of sigmoidal responses has seen good success in other domains (Kubassova
 255 et al. 2007), and accordingly we seek a good fit to the early part of these curves by functions
 256 of the form

$$f(x) = \begin{cases} 0, & x \leq x_0 \\ m(x - x_0), & x_0 < x \leq x_1 \end{cases} \quad (1)$$

257 where the parameters x_0, x_1 give the start and end of the ‘linear’ upward segment, and
 258 $m > 0$ is the gradient. It is straightforward to minimise, in the least squares sense, over
 259 these parameters for a given signal. Supposing an observed signal is $y = (y_1, y_2, \dots, y_T)$, and
 260 f is defined by equation 1, then we perform:

261 **Algorithm:** Determine best fit piecewise linear approximation

- 262 1. Set $x_0 = 1$.
2. For x_1 in the range $[x_0 + 1, T]$, determine

$$m_{x_0} = \max_{x_1} \frac{y_{x_1}}{x_1 - x_0}$$

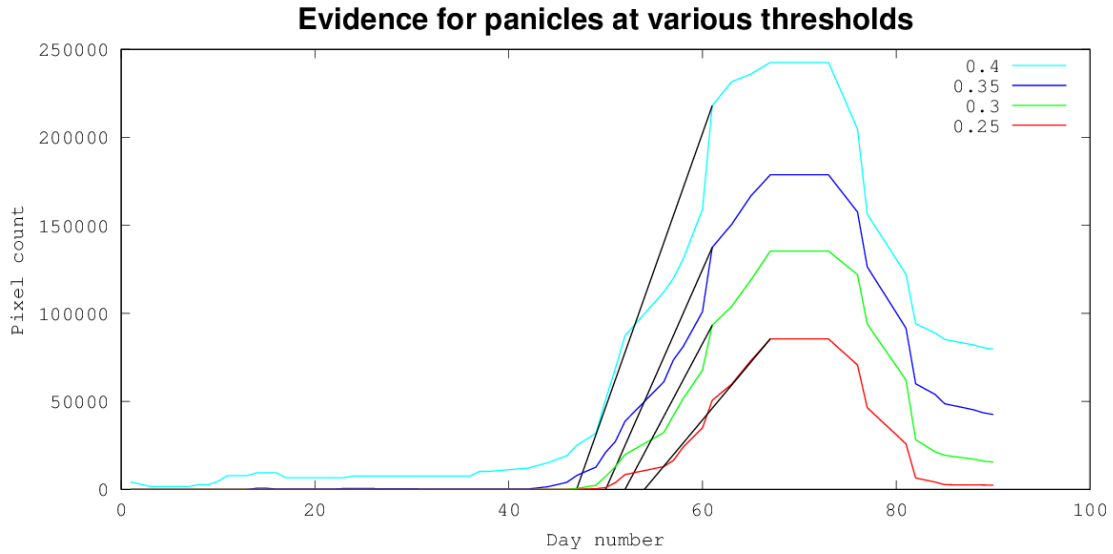
263 the linear approximation following x_0 of maximal slope. For x_1 giving this maximal
 264 $m = m_{x_0}$, set $E(x_0)$ as the MSE between y and f so defined in the interval $[1, x_1]$.

- 265 3. While $x_0 < T - 1$, set $x_0 = x_0 + 1$ and go to 2.

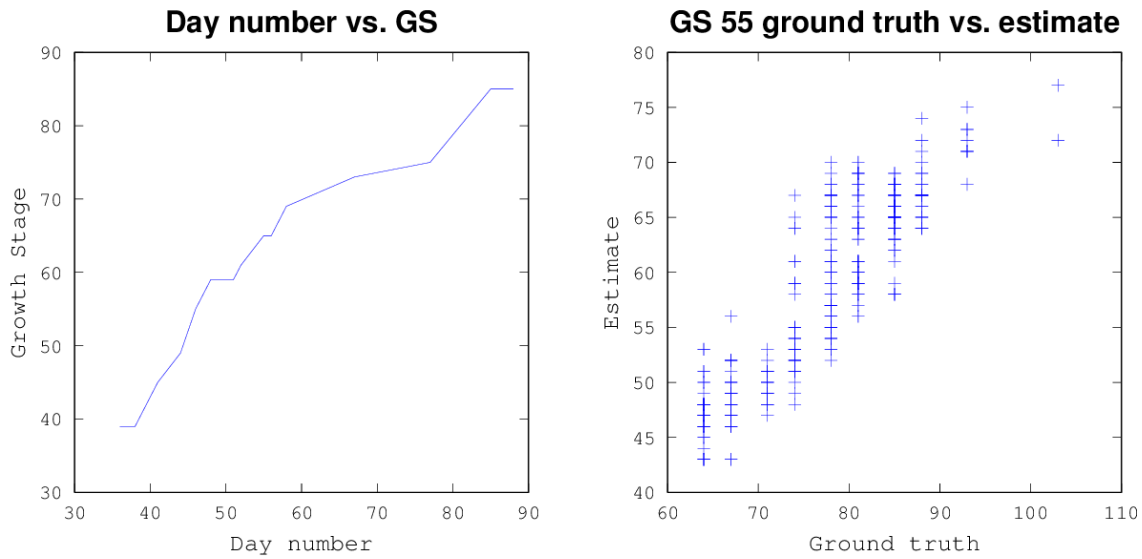
4. Determine

$$\hat{x}_0 = \arg \max_{x_0} E(x_0)$$

266 as the best performing offset. Use this value, and the associated x_1 determined in step
 267 2.



(a) Number of pixels giving certain strengths of response over time measured in experiment days – colours correspond to those of Figure 8. Black lines give LSQ best linear approximation to initial increase.



(b) For the primary tiller of a particular plant, GS plotted against day. For the 3 week period between days 40 and 60, more than 1 GS per day is being achieved.

(c) Observed GS 55 plotted against the proposed indicator – the correlation coefficient is 0.89 and the best line gradient 0.87.

Figure 9: Graphs of experiment and observation

268 We perform this algorithm on the signals extracted from the thresholded Hellinger distance
269 images which are median filtered to reduce the (considerable) noise that they inevitably
270 display.

271 There are clearly many ways this algorithm could be amended and improved, and the results
272 which follow may accordingly be seen as a low water mark for success. Figure 9a depicts
273 these line segments for four representative signals derived from one plant. In this example,
274 the values of x_0 are 45, 48, 51 and 54 days.

275 We have experimented using the value x_0 for various distance thresholds as an indicator of
276 GS. Our experiment was ground-truthed for GS 55 for some 270 plants and we have correlated
277 these observations with this predictor for the arbitrarily chosen distances 0.4,0.35,0.3,0.25
278 (illustrated in Figure 8 and 9a). Of these, the distance 0.3 provided a correlation coefficient
279 of 0.89 with ground truth – this is illustrated in Figure 9c. We are not predicting GS 55 in
280 any absolute sense although the **slope of the linear regression** is 0.87 which is encouraging
281 close to 1. **The mean offset (underestimate) of 8.9 days would be added to the predictor to**
282 **acquire GS55.**

283 Collecting ground truth is labour-intensive, and so observations are only made every 2-4
284 days (this is clear in Figure 9c). Simultaneously, judgement of GS with precision by one
285 individual, howsoever experienced, is very difficult to implement consistently over time and
286 across seasons. **Thus we can argue that the imperfect correlation we see (notably at ground**
287 **truth 80) might well be considerably better as errors in GS 55 observations could very easily**
288 **be up to 4 days.** For one plant, we have ground-truthed estimates of GS, plotted in Figure
289 9b; we believe the patterns in these observations to be characteristic. GS increases by more
290 than 1 per day over a 20 day period, then slows, then accelerates again as senescence sets
291 in. During periods of high gradient we might expect estimates from image data to be less
292 reliable, and stage 55 falls within this sensitive interval, further jeopardising accuracy. **It**
293 **is plausible to expect that mean observations of replicates of experimental conditions, for**
294 **example over different genotypes, would further reduce inaccuracies in the predictor.**

295 5 Conclusions and further work

296 We have demonstrated an approach to identification of oat panicle spikelets in the bulk col-
297 lection of images of developing plants. The algorithms deployed adopt the usual classification
298 approach of training on known data, and use a variant of the widely used and robust Local
299 Pattern texture detector. **All codes were written in standard, portable Matlab³ or C⁴. The**
300 **time required to process a single image is negligible – a small fraction of a second – and the**
301 **time to process a series of images for a plant and deliver a prediction correspondingly tiny.**
302 **Manual ground-truthing, of course, is very costly in resource.**

303 Significant success in identification of image regions with young spikelets can be evidenced.
304 This success can be reinforced by deploying obvious and justifiable domain knowledge such as
305 confidence that panicles will appear in the upper part of the plant, and will almost certainly
306 be enhanced by further experiments on a fully commissioned system delivering higher quality,

³MATLAB is a registered trademark of The MathWorks, Inc.

⁴The authors are happy to share codes on request.

307 consistent images. We also demonstrate the ability to detect second and subsequent flowering
308 tillers, permitting automated determination of the range of commencement of flowering on
309 a plant and its duration.

310 The detector has been exploited to predict a day on which growth onset commences; this
311 measure shows good correlation with ground-truthed GS 55 for a large sample. It is highly
312 probable that this correlation can be improved by refinements to the detector and better
313 measurement.

314 We have reported here work in progress, which we can be developed in several directions:

- 315 • The detector we have built was – albeit successful – the first and simplest experiment.
316 Extending this to more sophisticated variants is an obvious avenue of research: a
317 finer quantisation of the ‘circle’ surrounding the target pixel, and/or a finer colour
318 model, may improve performance and open the possibility of estimating the precise
319 numbers of spikelets present. It is moot whether the implied significant growth in
320 dimensionality would be worthwhile. **It is also possible that entirely different texture
321 analysis techniques, or exploration of colour spaces other than RGB, would assist.**
- 322 • The indicator we derive from the detector is open to significant improvement. At
323 least, the fitting to Equation 1 may be made much more robust in a number of ways
324 (RANSAC (Fischler & Bolles 1981) is just one). More constructively, optimal extrac-
325 tion of day from thresholded signal, and optimal choice of threshold given this, may
326 both be explored with every likelihood of improving results.
- 327 • The imaging system usually captures more than one view of the plant at each visit
328 to the cabinets. Routinely, this is a side view at 0, another at $\frac{\pi}{2}$, and a third, top-
329 down, view. We have performed no experiments on the top-down views but it is highly
330 plausible that the two side views, coupled with the knowledge that spikelets represent
331 a cluster in 3-space, would allow a 3-D reconstruction of the volume(s) occupied by
332 the clusters.
- 333 • More generally, in all the image sequences we collect, the temporal evolution of the
334 plant is of interest. Clearly, if a panicle is evident on a given day, it may be ex-
335 pected to be present in a similar location the next day, thereby easing and encouraging
336 identification. More interestingly, in pinpointing GS, we might possibly deduce likely
337 evidence the *preceding* day as well (this *forward-backward* reasoning has seen success in
338 plant imaging elsewhere (Li et al. 2013)). As mentioned above, the trivial foreknowl-
339 edge that panicles form above the (vertical) mid-point of the plant would immediately
340 assist measurements.

341 There remains interest in tracking the development of the panicle after GS 50-60. As
342 is evident from Figure 8, the detector we present here, by design, highlights the earlier
343 stages. Approaching Stage 70 the spikelets are almost exclusively yellow (see Figure 4),
344 and the detector fails to ‘see’ the panicle. We have experimented with a detector trained
345 on these which showed only modest success since the much simpler local patterns do
346 not provide the discrimination of the red/green patterns. We are confident that this
347 problem is amenable to efficient solution by using geometric foreknowledge (Stages 60+
348 must succeed Stages 50-59), and more complex colour or filter design models

- 349 • The emergence of anthers is another point of interest during panicle development –
350 GS 65 represents 50% of the primary tiller’s anthers being mature. In some plants
351 this is visually observable, but in oats anthers are very slender and difficult to observe
352 with any reliability in the images we acquire. Nevertheless, we are optimistic about
353 pinpointing stages in excess of 70 as the spikelets yellow, which would then allow some
354 interpolation of GS 65 given the work outlined above.

355 While this work is of direct benefit in existing experiments and high throughput installations,
356 we see it further as an exemplar of the practicality of applying established computer vision
357 techniques in plant breeding and biology. As is customary in cross-disciplinary work, it is
358 critical for the computer scientist to engage properly with what the domain experimenter is
359 trying to find out: thereafter it is possible that information automatically extractable may be
360 of great benefit, but may not correspond directly with traditional approaches. Specifically,
361 we suspect that Growth Stages habitually measured by hand may not be the simplest to
362 extract automatically, but a reproducible and reliable identification of other criteria would
363 prove to be of equal or more value.

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