

# **IMAGE PROCESSING FOR EARLY DETECTION OF LIVESTOCK DISEASES**

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Master in Mathematical Engineering

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## INTRODUCTION

African swine fever (ASF) is a devastating haemorrhagic fever of pigs that causes up to 100% mortality (Penrith et al., 2004b). It is arguably the most serious constraint for pig production whenever it occurs. Moreover, this matter is of great importance due to its remarkable potential for transboundary spread, as it was demonstrated in a largely manner during the second half of the last century when it escaped from Africa to affect Europe, Caribbean, Brazil and the Caucasus (Penrith, 2009).

Since ASF was re-introduced into Eastern Europe in April 2007, the disease has spread through five countries, drastically changing the European ASF situation. This re-introduction has significant implications for the affected countries, and it puts the European Union (EU) at serious risk of ASF introduction. All these risk factors are driven in turn by socio-economic, political and cultural factors (Sánchez-Vizcaíno et al., 2013).

No vaccine exists to combat this virus. The EU has allocated however a substantial amount of funds for research on vaccines for ASF through the sixth and seventh framework research project but there is no successful candidate vaccine yet (European Commission, 2016). Late detection of emergency diseases causes significant economic losses for pig producers and governments (Martínez-Avilés et al., 2015). Making the development of strategies, tests and tools to help with early detection of ASF an imperative mission.

The footage provided contains 23 days of surveillance taken with a surveillance camera with night-vision integrated fixed in a corner of the room which received fixed lighting. The videos show 8 pigs contained within a “U” shaped pen (see Figure 1). During these videos it is possible to see different levels of movement coming from the herd, as they perform different activities, like fighting, sleeping, feeding and interaction with humans among others. The footage covers three stages in the experiment: healthy, infection and ill. Providing an excellent opportunity to study their normal behaviour before the infection during and after it, in order to learn from them and detect the infection during its earlier stages to prevent it from spreading and thus saving the rest of the herd. However, this work has its focus on the imagery analysis taken from the video footage and behavioural classification of the herd.



*Figure 1 - A sample frame taken from one of the videos displaying the 8 pigs of the herd contained within a "U"-shaped pen.*

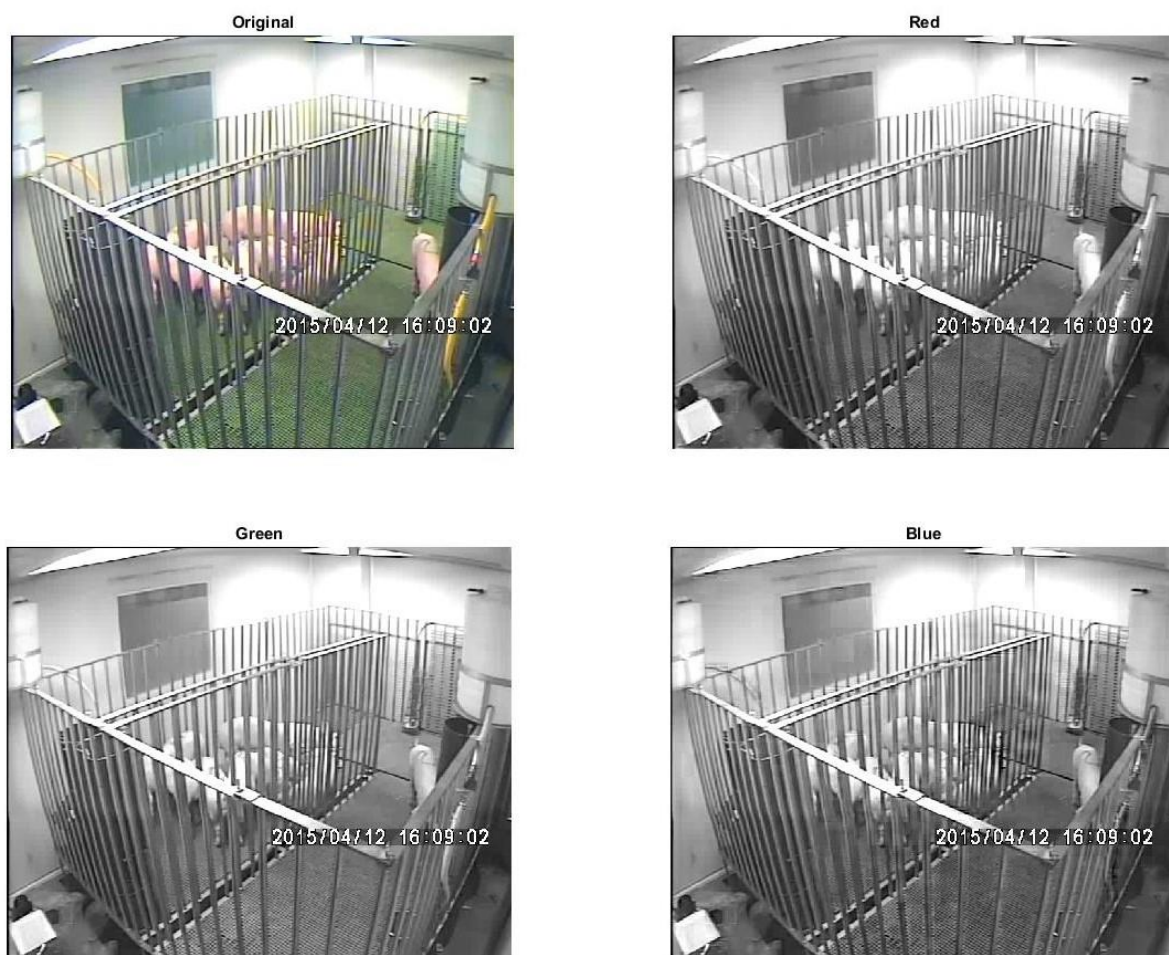
The surveillance videos provide excellent material to complete our task yet some considerations hinder an optimal analysis. First, the pen itself provides partial censoring of the images caused by the jailed construction (see Figure 1). Second, the "U" shape of the pen allows for pigs to block each other. Third, the limited pen size encourages the compaction of the herd in points which would render the individual swine detection as a project on its own. Fourth, the low video quality produces blurred images and changes in contrast between consecutive frames which derives into white noise. On the other hand, we find a fixed camera filming the same background during the entire tape and enough contrast easily to distinguish between animals and the background. Besides, the videos were recorded 24 hours in a row per day where the light changed twice a day: from 7 a.m. to 9 p.m., the room was artificially illuminated without any changes in intensity; from 9 p.m to 7 a.m. where the room was not illuminated but the camera recorded through night vision.

This work aims to compute the global motion of the whole herd between frames during the period of study as well as to classify the herd's activity in order to identify animal behaviours and to ascertain significant motion reduction in infected animals by ASF. This report is divided into three main sections: image and video processing, in order to enhance blurring and contrast of images as well as to reduce white noise; a description of the Optical Flow Algorithm used to detect and measure motion in the footage and the total motion measurement per time unit; and, the classification of motion in the herd so as to identify different animal behaviours.

## DATA AND IMAGE ENHANCEMENT

Our data was collected by a fixed camera which recorded 24 hours per day during 23 days. The image and video processing as well as the posterior analysis were carried out with Matlab 2014b.

In order to perform a good motion estimation between frames, we previously processed individual images to increase animal detection. The video presents 6 frames per second and each frame we would process as an image of 704x576 pixels. The video format is 'RGB24'. We started by decomposing each video frame into red, green, and blue (RGB) channels in order to determine the one displaying the sharpest image as shown in Figure 2.



*Figure 2- The original image was decomposed into its RGB channels. It can be appreciated that the red channel shows the sharpest image of all three channels.*

As we can see on the figures above, the image with the best definition is that corresponding to the red channel which showed better differentiation between animals (pink coloured) and the ground (green). Furthermore, working with only channel allow to save computational time. Afterwards, in order to improve the result obtained on the red channel, we modified its contrast and sharpness.

First, we used the *imadjust* command to adjust the contrast. First, we kept the default configuration acquiring the result displayed on Figure 3.



*Figure 3 - This picture shows the results obtained by the automatic contrast adjustment suggested by the *imadjust* command.*

As Figure 3 shows, there was little improvement in the image. Thus, we manually configured the contrast of the image by fixing its lower and upper thresholds. Figure 4 shows a comparison between two contrast configurations that we chose. As displayed, the best result was found by fixing the lower and upper thresholds to 0.2 and 0.8 respectively.



*Figure 4 - Comparison of two different manual contrast configurations.*

The contrasted image allows better differentiation between animals (pink colour) and the wall (nearly white). The worse motion following on the lightning areas with only Red Channel is partly solved with the contrast.

We also tried to enhance the results obtained previously by treating the images' sharpness, for which we used the *imsharpen* command. We can observe on the Figure 5 that the sharpened image is better defined than the original one as it defines better the difference between white background and lightest pink on animals:



Figure 5 - Sharpness comparison between the original red channel and the enhanced one.

Moreover, we observed that there was white noise created by the camera working, which we also attempted to rectify as we explain in the Animal Behaviour section of this report. Noise in the background was especially problematic for our task due to our intent to measure motion, it could have created the sense of false motion strong enough to be noticed by the algorithm and therefore it would have corrupted our results. We approached this problem by creating a mask for the image that deleted the background of the frame and focusing the study only to the movement generated within the cage.

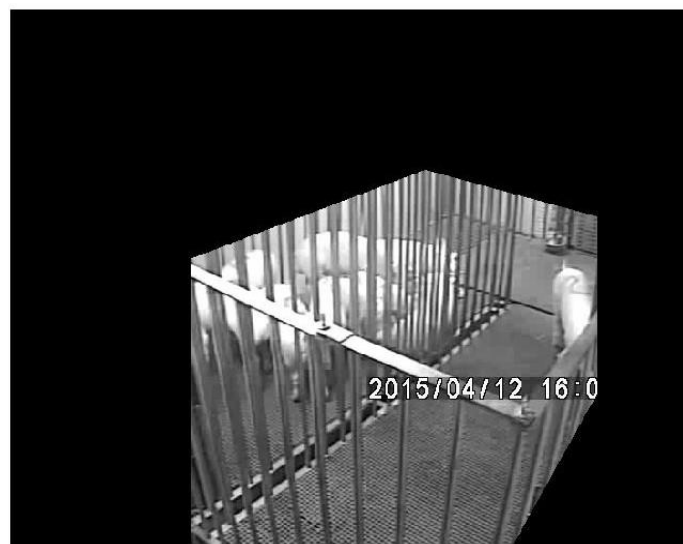


Figure 6 – Image treated and mask used.



Our next steps included dividing each cage with a different mask and study each cage separately, which could not be implemented because of the time constraints imposed by the duration of Modelling Week.

## OPTICAL FLOW ALGORITHM

Optical flow is defined as the change of structured light in the image, e.g. on the retina or the camera's sensor, due to a relative motion between the eyeball or camera and the scene. The goal of the method is to compute an approximation to the 2-d motion field (a projection of the 3-d velocities of surface points onto the imaging surface) from spatiotemporal patterns of image intensity (Barron et al., 1992).

For convenience and for simply the problem, the algorithm assumes a particularly simple world where the apparent velocity of brightness patterns can be directly identified with the movement of surfaces in the scene. Also, it assumes at first that reflectance of the surface varies smoothly and has no spatial discontinuities. This latter condition assures us that the image brightness is differentiable. Computing the velocities of points on the object is a matter of simple geometry once the optical flow is known (Fleet et al., 2005). Thus, we started computing optical flow basing on the Optical Flow (Barron et al, 1992; Meinhard-Llopis, 2013) and Horn-Schuck method (Horn at al., 1981).

We first read the video with Matlab command *VideoReader*, and get the information of it. We applied the image treatment that we developed on the Data Point. Once we had the video prepared we analysed motion frame by frame. In each step we considered the current frame and the one before. As we told before, the frames are represented by a matrix with image size. Using this information we created vectors  $dx$ ,  $dy$ ,  $dt$ ,  $U$  and  $V$  of zero matrix image size. We also created  $uvect$  and  $vvect$  which are vectors with size the number of Frames.

We fixed some initial parameters like Maximum Number of Iterations of the algorithm (MaxIts = 25). Calculating EnR as it follows:

$$\text{EnR} = \text{Min} (1, 0.92 + 0.1 * \text{MaxIts} / 100);$$

We used it to calculate Kernel smooth as:

$$\text{Kern} = \begin{pmatrix} 1 & \sqrt{2} & 1 \\ \sqrt{2} & 0 & \sqrt{2} \\ 1 & \sqrt{2} & 1 \end{pmatrix}$$

$$\text{Kern} = \text{EnR} \frac{\text{Kern}}{\sum \text{Kern}}$$

We use Kernel on the main steps of the algorithm. Note that Kernel is normalized with EnR. As the Maximum number of iterations go up, EnR would get closer to 1. Kernel would be a smoothing for approach the results to the one using the original formula.

On the next steps we started using the algorithm. We made the following steps for each frame of the video record. We read the new Image, and save the previous one as *imPrev* and this new one as *imNew*. Considering  $\text{im} = \text{imPrev} + \text{imNew}$ , then we have  $dx = \frac{dl}{dx}$ ,  $dy = \frac{dl}{dy}$  and  $dt = \frac{dl}{dt}$ . Our  $u$  and  $v$  would be  $u = \frac{dx}{dt}$  and  $v = \frac{dy}{dt}$ . It would be matrixes of the derivatives of the image and it would represent the vertical and horizontal motion matrixes of the Optical Flow. The aim of the algorithm is calculating that matrixes and the mean value of them for each frame, so we have a measure which represents the movements of the animals.

In general method, the vector field  $(u, v)$  satisfies pointwise the following linear condition, which is derived from the brightness constancy assumption by applying the chain rule:

$$(dx, dt) \cdot (u, v) + dt = 0$$

This is the optical flow constraint equation. The difficulty resides in the impossibility of solved this equation pointwise.

Therefore, our aim is obtaining  $u$  and  $v$  matrixes and their mean values (which would be saved on *uvector* and *vvector*). For that we started with the Horn and Schunck method. The propose of it consists in formulating the problem of optical flow as a variational problem, where the desired vector field  $(u, v)$  is defined as the minimizer of certain energy functional,  $H$ .

$$H = \int (dx u + dy v + dt)^2 + \eta^2 (|\nabla u|^2 + |\nabla v|^2)$$

Where  $\eta$  is a parameter control that we fixed as 10.

The minimization of  $H$  could be treated with Euler-Lagrange equations:



$$\begin{aligned} dx^2 u + dx dy v &= \eta^2 \operatorname{div}(\nabla u) - dx dt, \\ dx dy u + dy^2 v &= \eta^2 \operatorname{div}(\nabla u) - dy dt. \end{aligned}$$

Solving that equations and rearranging terms we can obtain  $u$  and  $v$  vectors with:

$$\begin{aligned} u &= \bar{u} - \frac{dx (dx \bar{u} + dy \bar{v} + dt)}{\eta^2 + dx^2 + dy^2} \\ v &= \bar{v} - \frac{dy (dy \bar{u} + dx \bar{v} + dt)}{\eta^2 + dx^2 + dy^2} \end{aligned}$$

in where  $\bar{u}$  and  $\bar{v}$  are obtained as it follows:

$$\begin{aligned} \bar{u} &= u * \text{Kern} \\ \bar{v} &= v * \text{Kern} \end{aligned}$$

with  $*$  meaning mathematical convolution.

The last step would be calculating the mean vertical and horizontal motion of each frame. We would save all the values in  $u\text{vect}$  and  $v\text{vect}$ . An image of the result of motion in two different frames could see in the Figure it follows:

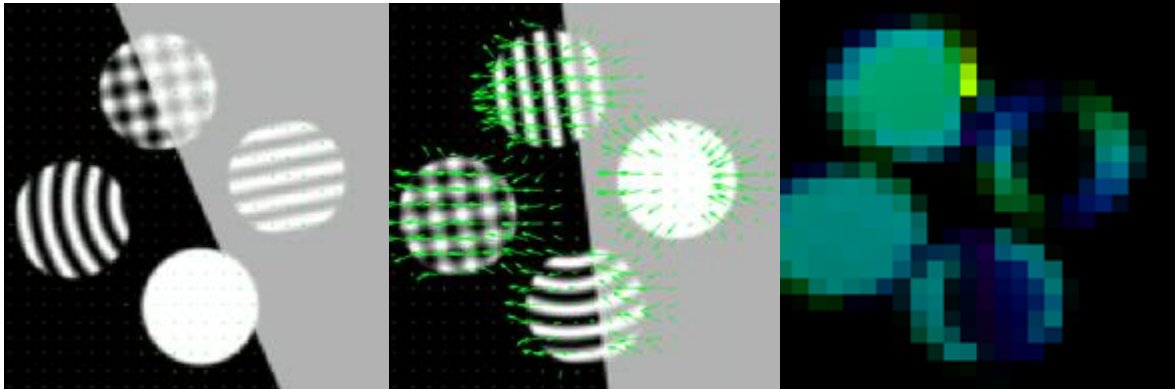


Figure 7 – Computational treatment of Motion.

## MOTION MEASUREMENT

In the chapter before we obtained for each frame two vectors of movement  $(u, v)$ , where the size of these vector are the number of pixels in a frame. In order to work better with this vectors, we transformed them in matrices of size  $n \times m$ , where  $m = n^{\circ}pixels$ .

Therefore, we have for each frame  $t$  two matrices  $U_t$  and  $V_t$  that give us information about the horizontal and vertical movements of the pigs. The elements of these matrices,  $u_{t_{px}}, v_{t_{px}}$  represents the horizontal and vertical motion in each pixel  $px$ . We can obtain then a measure of motion for a pixel as the norm.

$$m_{t_{px}} = \sqrt{u_{t_{px}}^2 + v_{t_{px}}^2}.$$

In order to measure the global the motion of a partially selected frame, we compute the motion of a frame as the mean the motion for all pixels.

$$m_t = \frac{1}{n} \sum_{px}^n m_{t_{px}}$$

This metrics allows us to obtain an unique motion value per frame, that is at time  $t$ . Thus, each video builds a temporal series, which will have as many values as the number of frames of the video. In the Figure 8 we can see a temporal series obtained from a video of two hours.

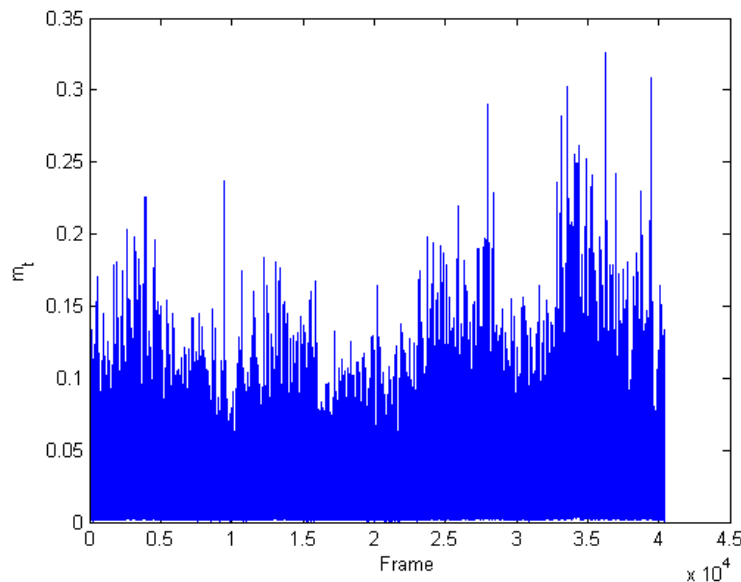


Figure 8 – Representation of temporal series (duration: 120 minutes).

We realize that these series are difficult to manage with, so we are going to work with the moving average and moving variance series.

## ANIMAL BEHAVIOUR

Because of computational constraints we could not obtain the temporal series of all the videos recorded. Instead, we analyze some videos with different herd motion in order to distinguish several types of motion. In the first one the pigs are sleeping or lying and there is no appreciable motion, the second one is a video of normal motion and the last one is a video of the human interaction with the pigs. In all of these videos they were not infected yet. Our aim is to distinguish between these behaviors and the behaviors when they are infected.

### Sleeping-Lying (no motion, only Noise)

There are some abrupt light changes in the videos that are probably occasioned by a camera default. From now on we are going to refer to these light changes as noise. Our aim is to study these disturbances in the images in order to distinguish this noise from the motion.

We choose a video where pigs are sleeping. Because there is no appreciable motion, all the motion obtained is the temporal series showed in the Figure 9. In this graphic the x vertices represent the number of frame and the y vertices are the value of  $t$ , the measure of motion of the frame. We can observe two series in the image: the blue series is the original series and the red one is the moving average series.

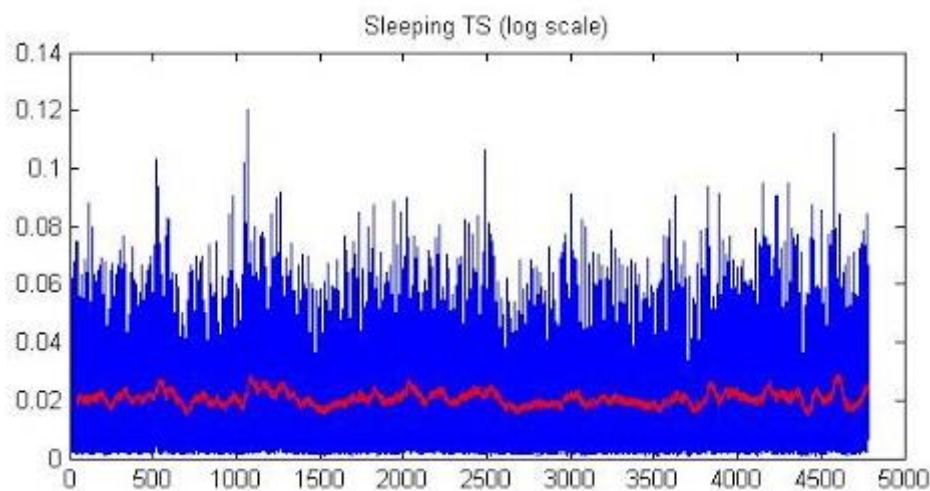


Figure 9 – Sleeping motion representation. The red series represents the moving average series and the blue one the original series.

We are going to study the moving average series. We are interested in applying a Control Charts to measure and understand the variability of a process (Kang, et al 2011). We are going to use the Shewart Control Charts (Murdoch, et al 1979), which requires that this variability follows a normal distribution. Indeed, the noise follows a  $N(0.0205, 0.0018)$  (Kolmogorov-Smirnov test,  $p < 0.01$ )

In the Shewart Control Chart we obtained two outer limits:  $\mu + 3\sigma$  as the Upper Control Limit (UCL) and  $\mu - 3\sigma$  as the Lower Control Limit (LCL). These outer limits are probability limits which assures us that the probability of a sample point falling outside the interval (LCL, UCL) is very small.

In our case we are interested only in the Upper Control Limit: if the motion measure ( $m_t$ ) is above the UCL we will say that there is motion in the video. Let's look at an example to understand better how it works.

The Figure 10 shows the moving average series obtained from two different videos: in the green one the pigs are asleep the red one is the previous series of pigs sleeping.

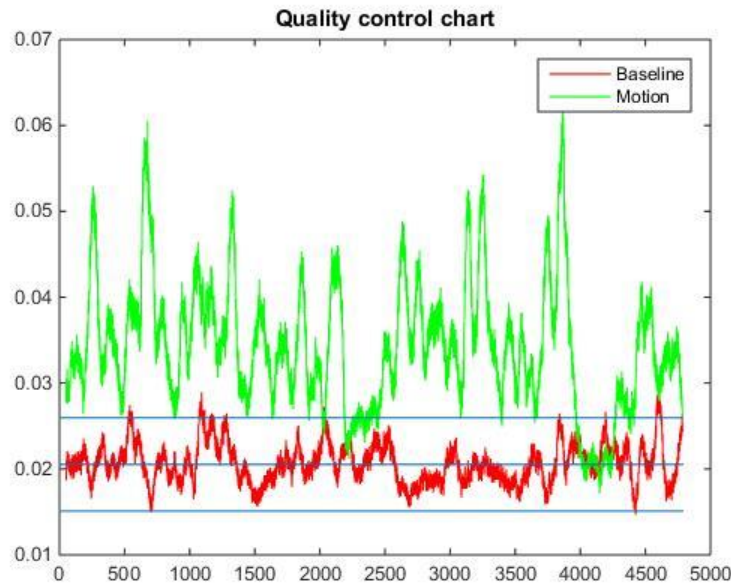


Figure 10 – Comparative of moving average with motion and sleeping behaviour. It is also marked the UCL and the UDL motion series.

We can observe that sometimes the motion of the green series is below the UCL but we see these moments of the video and we realized that they were resting at those moments.

## Feeding-Walking and Human interaction (significant motion variations)

For the rest of behaviour we have taken a video on the first days where the herd is not infected or sleeping and their motion is normal. From this video there are several differences such as when they are feeding, playing or fighting. Also there are just some of them who are walking. A deep analysis could be able to classify when they have more activity. In our case we will just classify when they have high or normal activity.

From this video we took ten minutes, 3600 frames, and we computed the corresponding time series. As we did before, we computed the moving average motion which measures the variation, on average, within the last 50 frames. It is also showed the moving variance motion that gives us similar information about the motion of the herd. This time series is less impressionable by the scale of brightness among different videos. From both of them we calculate their averages as average motions of this behaviour.

In some loaded videos by us we can see there are human interactions when the veterinarians are in the jail with the herd. The levels of motion are upper to the shown above. There are motion from the herd and motion from the veterinarians that fill a bigger part of the record than the herd. As we did with the other videos we took ten minutes and we computed the moving average motion and the moving variance motion and their corresponding average.

On the next figure we shows the differences between the moving average motion and moving variance motion from the behaviour which we were talking about:

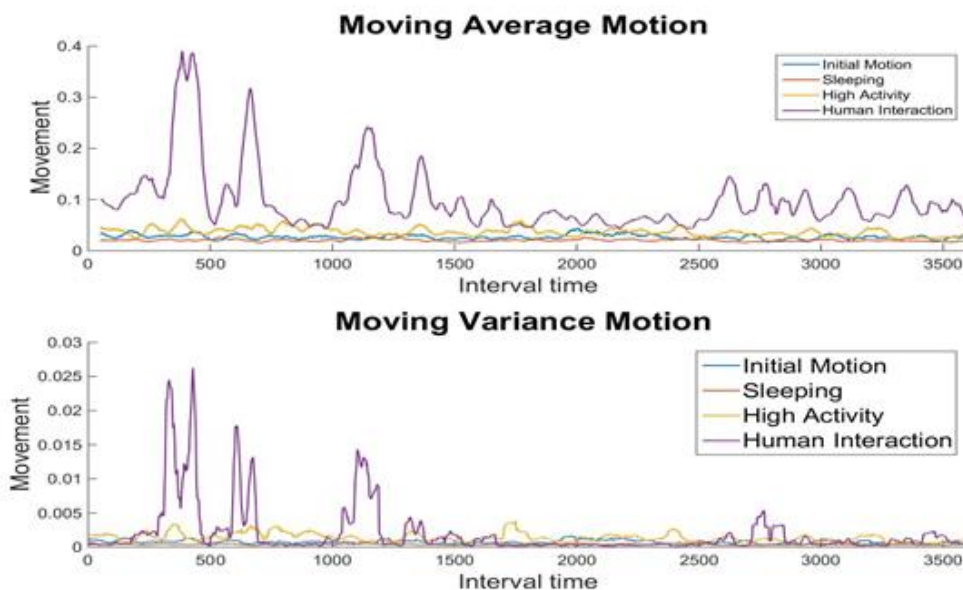


Figure 12 – Different Animal Behaviours Graphic.

As expected the purple line is up to the others in moving average motion because the activity on this period is higher than in the others. It is not as clear always in moving variance motion that it shows us significant differences in the motion during the video. As we saw, the orange one is when the herd were sleeping, and in the moving average motion had some fluctuations that we call noise, in the moving variance motion is almost a straight line around zero. There is a significant difference between the yellow and the blue line, where they were playing or feeding and where they were just walking or not all the herd was in motion, easier to see in the moving variance motion.

## Algorithm

According to this behaviour we have created a model that given a video it classifies for every minute which kind of motion they have. It takes the time series and computes the moving variance motion, because we find best results with this one and have large differences among the behaviour, and it compares the average which it is obtained from the different behaviour that we defined above. It assigns one number from 0 to 3 in order to the quantity of motion – it has been 0 sleeping, 1 walking, 2 high activity as feeding or playing, and 3 humans interactions- taking the minimum distance from this minute of recording to our groups.

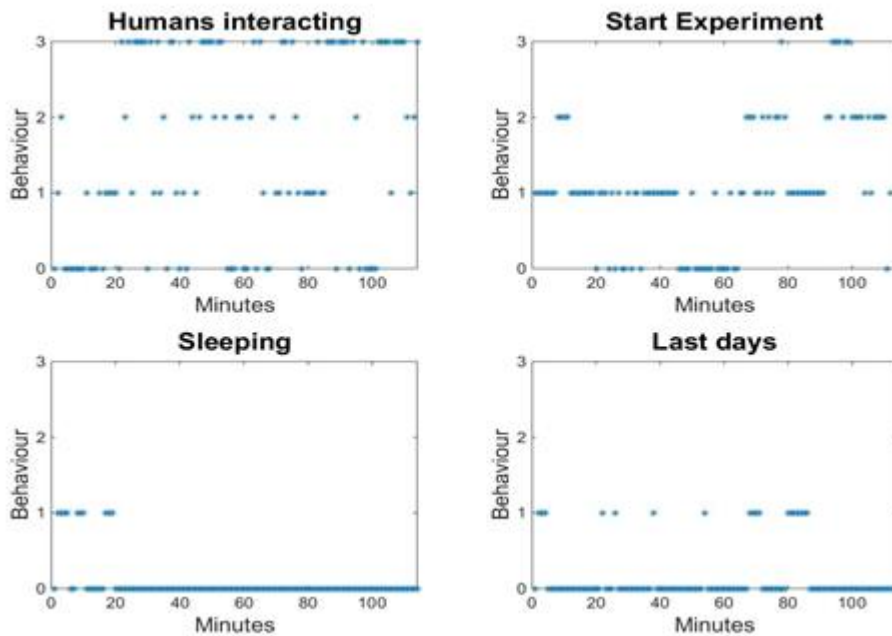


Figure 13 – Behaviour classification of the herd on different videos.

## CONCLUSION

Using our algorithm we are able to classify the motion in each video in intervals of one minute. Future improvements based on this work should define new behaviour, as we commented before, for example, identify when they are playing or feeding or fighting, and test it. It is also important to test it for the whole experiment in order to study the complete evolution of the data, in our case we can just check it in four videos because of time constraints. Nonetheless we loaded four different videos, two hours of duration each one, in some parts of the experiment.

In one of them we get human interactions and in another one the herd is sleeping. The others two are filmed at the same hour, one before our herd was infected and another one after that. In the next figure we can see the obtained results:

In human interacting there is a huge part of threes that is the group of human interaction, there are also some zeros because we are using the variance and if the level of motion is more or less the same during this minute our model gives the lowest value.

In the video in which they are sleeping we can see how at the beginning there are some pigs that are not fall asleep yet but after that there is no motion.

Between the videos from the beginning of the experiment to the end, we observed how motion levels are lower in the last days, probably if we test it for some videos between this both we can see how levels of motion are decreasing gradually.



## REFERENCES

- [1] Penrith, M-L., Thomson, G.R. & Bastos, A.D.S. 2004b. "African swine fever", *Infectious diseases of livestock*, 2nd ed., edited by J.A.W. Coetzer & R.C. Tustin. Cape Town: Oxford University Press.
- [2] Becker, Y.. "African Swine Fever", *Developments in Veterinary Virology*, Springer Science & Business Media, Dec 2012, Martinus Nijhoff Publishing.
- [3] Penrith, M. L.. "African swine fever", *Onderstepoort Journal of Veterinary Research*, 76:91-95 (2009).
- [4] José Manuel Sánchez-Vizcaíno, Lina Mur, Beatriz Martínez-López, "African swine fever (ASF): Five years around Europe", *Veterinary Microbiology Vol. 165*, Issues 1-2, p.45-50, July 2013, Elsevier.
- [5] European Commission, "Health and Consumers: African Swine Fever", [ec.europa.eu/food/animals/animal-diseases/control-measures/asf/](http://ec.europa.eu/food/animals/animal-diseases/control-measures/asf/), June 2016.
- [6] Martínez-Avilés, M. and Fernández-Carrión, E. and López García-Baones, J. M. and Sánchez-Vizcaíno, J. M., "Early Detection of Infection in Pigs through an Online Monitoring System", *Transboundary and Emerging Diseases*, 1865-1682, May 2015.
- [7] Barron, J. L., D. J. Fleet, S. S. Beauchemin, and T. A. Burkitt. "Performance of optical flow techniques". *CVPR*, 1992.
- [8] Horn, B.K. P. and B. G. Schunck. "Determining Optical Flow", *Artificial Intelligence, MIT, vol 17*, pp. 185-203, 1981. -Llopis
- [9] Meinhardt-Llopis, E., Sánchez, J. and D. Kondermann. "Horn-Schunck Optical Flow with Multi-Scale Strategy". *Image processing On Line*, 2013.
- [10] Kesrarat, D. and V. Patanavijit. "Tutorial of Motion Estimation Based on Horn-Schunck Optical Flow Algorithm in MATLAB". Review Article.
- [11] Fleet, D.J. and Y. Weiss. Optical Flow estimation. *Handbook of Mathematical Models in Computer Vision*, Chapter 15, pp. 239-258, Springer 2005.
- [12] <http://es.mathworks.com/discovery/optical-flow.html>
- [13] <http://es.mathworks.com/products/image/features.html#mejora-de-la-imagen>
- [14] Kang, C. W. and Kvam, P. H. (2011) *Shewhart Control Charts*, in *Basic Statistical Tools for Improving Quality*, John Wiley & Sons, Inc., Hoboken, NJ, USA.  
doi: 10.1002/9781118491751.ch5
- [15] Murdoch, J. (1979). *Shewhart Control Charts*. In *Control Charts* (pp. 36-55). Macmillan Education UK.