

Sheep Behavioral Analysis with Optical Flow

Análise Comportamental de Ovinos com Fluxo Óptico

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Abstract: Determining behavioral deviations in sheep is challenging through visual observation alone, as sheep are generally stoic animals and may not easily show signs of pain or discomfort. This study aimed to evaluate and classify activity changes in sheep using optical flow algorithms as an alternative approach. Video recordings of 32 sheep housed in 8 pens were analyzed over 4 days, with each day consisting of 4 one-hour video segments. These segments were manually observed at 5-minute intervals to document the time spent laying, standing, and walking. Simultaneously, the same video segments were analyzed using optical flow algorithms to track movement patterns. The calculated optical flow measures, including mean, variance, skewness, and kurtosis, were then correlated with the observed behaviors. These measures demonstrated their potential as effective tools for monitoring behavioral activity changes in sheep, providing an objective method to track behavior and detect deviations that might indicate discomfort, stress, or health issues.

Keywords: Precision Livestock Farming — Motion Detection — Optical Flow — Sheep Behavior

Resumo: Determinar desvios comportamentais em ovelhas é uma tarefa desafiadora, se feita apenas por meio da observação visual, pois as ovelhas são geralmente animais estoicos e podem não mostrar facilmente sinais de dor ou desconforto. Este estudo teve como objetivo avaliar e classificar mudanças de atividade em ovelhas usando algoritmos de fluxo óptico como uma abordagem alternativa. Gravações de vídeo de 32 ovelhas alojadas em 8 baias foram analisadas ao longo de 4 dias, com cada dia consistindo de 4 segmentos de vídeo de uma hora. Esses segmentos foram observados manualmente em intervalos de 5 minutos para documentar o tempo gasto deitado, em pé e andando. Simultaneamente, os mesmos segmentos de vídeo foram analisados usando algoritmos de fluxo óptico para rastrear padrões de movimento. As medidas de fluxo óptico calculadas, incluindo média, variância, assimetria e curtose, foram então correlacionadas com os comportamentos observados. Essas medidas demonstraram potencial como ferramentas eficazes para monitorar mudanças de atividade comportamental em ovelhas, fornecendo um método objetivo para rastrear o comportamento e detectar desvios que podem indicar desconforto, estresse ou problemas de saúde.

Palavras-Chave: Pecuária de Precisão — Detecção de Movimento — Fluxo Óptico — Comportamento de Ovelhas

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1. Introduction

Precision Livestock Farming (PLF) is an approach that utilizes technology and data-driven methods to optimize livestock production and management. It is gaining increasingly consideration for its capacity to collect data from animals, or groups of animals, analyze and implement precise actions to improve animal health, welfare, and overall farm efficiency [1]. This approach vastly relies on sensors to monitor and classify animal behavior, which are designed to collect real-time data

on various aspects of animal behavior, health parameters, and environmental conditions. The data obtained from these sensors is then used to make informed decisions and implement precise actions to optimize animal welfare and farm efficiency.

Optical flow is a non-contact method, that relies only on a camera, and provides means to analyze the movement by tracking the changes in intensity patterns between consecutive frames of video footage, allowing to estimate the speed and direction [2, 3]. By leveraging the data derived from optical flow

analysis, farmers can gain a deeper understanding of animal behavior and use this information to make informed decisions about their welfare [4]. Optical flow measures, such as mean, variance, skewness and kurtosis, are basic statistical properties that can be derived automatically and continuously [4]. Defining which statistical properties are most appropriate is the key step in using optical flow in precision livestock farming systems to monitor and assess the welfare of animals, by analyzing its motion patterns [5, 4, 6].

It is known that studies on behavioral traits are conducted mostly on cattle, with few studies conducted on sheep using contact-base methods [7, 8, 9, 1] and even less using non-contact sensing methods [10, 11]. In this study, optical flow is used to classify sheep behavioral activity as laying, standing and walking, the activities of interest, as defined in [1, 9].

2. Related Works

The use of sensors, like accelerometers, gyroscopes, magnetometers and radio-frequency identification, have been widely used in human activity studies to monitor, analyze and assist in the daily life [12]. The same technology can be used to monitor the health and welfare of livestock in Precision Livestock Farming (PFL). This sensor-based technology can be used to detect lameness in cattle and in sheep in an accurate and timely manner, minimizing the time needed to detect and treat this illness [9, 13].

In [4], optical flow was used to analyze the behavior of a large group of broiler chickens from video records. With the optical flow mean, variance, skewness and kurtosis they characterized the overall movement of the whole flock of chickens. The experiment was latter confirmed in [14] with multiple flocks of chicken from 6 farms, 1 in England and 5 in Switzerland. In [6], optical flow was used to correlate growth performance and flock activity of Pekin ducks with stocking densities, where optical flow mean and variance showed had significant relation with stocking densities. Optical flow was also utilized in [15] to monitor development of tail biting outbreaks in pigs and in [16] to detect activity changes in sows during final gestation. In both, the results obtained with optical flow were a promising tool for monitoring activities changes in pigs. In [11], Mask R-CNN was used to classify sheep behavior in laying, standing and free, obtaining 97% mAP in sheep detection and segmentation. In [10], sparse optical flow was used combined with machine learning algorithms to classify behavioral traits obtained from a sheep fear test, obtaining 100% of accuracy in detecting if a sheep is active or passive in front of a fear factor. However, optical flow has not been explored for monitoring and classifying activities of sheep in laying, standing and walking. In this study, dense optical flow was used to evaluate activity changes in sheep.

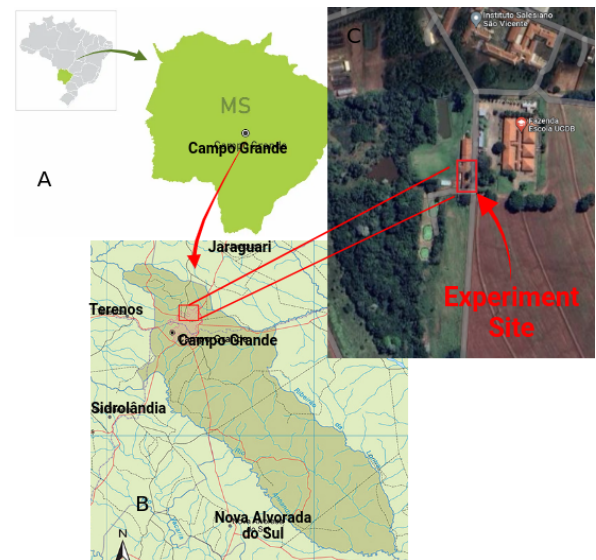


Figure 1. Location of the study area in Dom Bosco Catholic University School Farm, Campo Grande, Brazil.

3. Materials and Methods

In this section, our dataset is described and the utilized optical flow methods are presented in detail.

3.1 Dataset

The dataset used in this research was collected at the Dom Bosco Catholic University School Farm (see Figure 1), which houses 32 sheep of a genetic mixture of the Santa Inês and Texel breeds. These sheep, comprising 17 females and 15 males, were housed separately in 8 pens, each with the same layout. Each pen is a small enclosure of approximately 3 m², with 4 sheep per pen. The sheep were 1 year old at the time of the videos recordings, which were conducted on 4 different days in 2019, October 20th, November 8th, November 9th, and November 22nd. The recordings were made using a combination of artificial light and natural inside the corral, although ambient light in the area was somewhat limited. For this experiment, only 4 pens were selected, which can be seen in Figure 2, based on how long sheep remain visible in videos. To maintain the lighting standard in the recordings and the largest number of cameras, 4 periods were selected: (1) between 08:00 and 09:00; (2) between 10:00 and 11:00; (3) between 12:00 and 13:00; and (4) between 14:00 and 15:00. During each of these periods, 108,000 frames per hour were captured for each pen on every recording day, resulting in a total of 64 hours of video footage for analysis.

The activity of the sheep was evaluated through a manual scan sampling method, where 5 minutes of video were observed, followed by 5 minutes skipped. This approach was used to minimize potential bias and ensure more balanced observations. The sheep behaviors were classified into three main categories, based on definitions from [1]: standing, described as sheep standing on all four legs with or without jaw movement; walking, described as sheep moving forward



Figure 2. Sample frames showing the sheep and the conditions of the selected pens.

in a four-beat motion for at least 2 seconds with their head raised and aligned in the direction of the movement; and laying, described as sheep laying on the ground in sternal or lateral recumbency with or without jaw movement. The result of this analysis, as shown in Table 1, showed that sheep spent between 35.199% and 82.113% of the time laying, between 12.656% and 47.587% of the time standing and between 5.520% and 20.297% of the time walking every day in each camera. Across almost every day and in each camera's observations, the data reveal a tendency for the sheep to spend more time laying down than they did standing or walking combined. This finding suggests that laying is the most common activity among the sheep in the observed conditions.

Table 1. Sheep behavioral time budget on four different days for each camera. On October 20th, camera 5 was discarded because it contained too much noise.

		October	November		
		20th	8th	9th	22nd
Cam. 3	Laying (%)	63,020	49,410	75,666	53,910
	Standing (%)	27,604	36,438	17,555	40,165
	Walking (%)	9,375	14,150	6,777	5,924
Cam. 4	Laying (%)	78,958	66,232	57,158	49,652
	Standing (%)	15,520	22,748	31,277	42,129
	Walking (%)	5,520	11,019	11,563	8,217
Cam. 5	Laying (%)	X	35,199	52,029	35,964
	Standing (%)	X	45,522	33,226	47,587
	Walking (%)	X	19,278	14,743	16,447
Cam. 6	Laying (%)	82,113	42,203	61,538	48,170
	Standing (%)	12,656	37,500	32,265	41,585
	Walking (%)	5,230	20,297	6,196	10,243

Sheep spent more time laying between 12:00 and 13:00 and more time standing between 08:00 and 09:00 in cameras 5 and 6, between 10:00 and 11:00 in camera 3 and between 14:00 and 15:00 in camera 4. Sheep spent more time walking between 10:00 and 11:00 in camera 3, between 14:00 and 15:00 in cameras 4 and 5 and between 08:00 and 09:00 in camera 6, as shown in Table 2.

Table 2. Sheep behavioral time budget by hour in each camera.

		Hours of day			
		08-09	10-11	12-13	14-15
Cam. 3	Laying (%)	52,242	42,825	82,395	64,480
	Standing (%)	37,443	45,291	12,604	26,237
	Walking (%)	10,313	11,883	5,000	9,282
Cam. 4	Laying (%)	61,123	57,500	77,916	55,184
	Standing (%)	29,735	30,952	18,229	32,718
	Walking (%)	9,141	11,547	3,854	12,096
Cam. 5	Laying (%)	22,869	35,967	68,679	36,526
	Standing (%)	58,806	45,322	23,736	40,097
	Walking (%)	18,323	18,709	7,584	23,376
Cam. 6	Laying (%)	50,211	65,430	64,767	58,375
	Standing (%)	35,126	24,760	27,953	33,248
	Walking (%)	14,662	9,808	7,278	8,375

3.2 Optical Flow

The Optical Flow algorithm estimates the rate of change in brightness between two adjacent frames, calculating a velocity vector that represents the motion between the frames. This technique captures the movement of objects in an image from one frame to the next, which may be caused by the motion of the camera or the movement within the scene itself. Optical flow is typically represented as a 2D vector field, where

each element corresponds to the movement of points from one frame to another [17]. There are two primary types of optical flow: dense and sparse. Dense optical flow calculates the flow vector for every pixel in the frame, providing a detailed map of motion across the entire image. In contrast, sparse optical flow computes the flow vectors only for select pixels, such as those representing edges or corners of objects, making it more efficient but less comprehensive [18]. In this study, the goal was to analyze animal behavior, which necessitates examining the full body movement of the animals. Thus, it was important to compute the flow using all the pixels representing the animal's image, ensuring that subtle behavioral cues are captured. For this reason, dense optical flow, specifically the method proposed by [19], was selected. This approach is adaptable for use with various groups of animals and allows for more comprehensive behavioral analysis.

Farneback's algorithm [19] leverages polynomial expansion to approximate image patches and track their motion across frames. It assumes a constant motion vector within a local neighborhood. The polynomial expansion models the local intensity variation as:

$$I(x) \approx x^T A x + b^T + c \quad (1)$$

where A is a symmetric matrix (captures curvature), b a vector (captures linear terms) and c a scalar (constant term). Given two frames, $I(x)$ and $I(x+d)$, the algorithm estimates a motion vector d such that the intensity change is minimized:

$$I(x+d) \approx I(x) \quad (2)$$

Substituting the polynomial expansions of $I(x)$ and $I(x+d)$ into equation 2 and matching coefficients yields:

$$A_2 = A_1 \quad (3)$$

$$b_2 = b_1 - 2A_1 d \quad (4)$$

$$c_2 = d^T A_1 d - b_1^T d + c_1 \quad (5)$$

The key observation is that equation 4 provides a means to solve for the translation d , assuming that A_1 is non-singular. By rearranging equation 4, the translation d can be computed as:

$$\begin{aligned} b_2 &= b_1 - 2A_1 d \\ 2A_1 d &= b_1 - b_2 \\ d &= \frac{(b_1 - b_2)}{2A_1} \end{aligned} \quad (6)$$

This requires A_1 to be invertible, which is generally true for well-defined neighborhoods where local intensity variations are sufficient to constrain the motion.

Figure 3 illustrates the process of extracting optical flow in this study, where consecutive frames from the recorded video were used to calculate motion. For each minute of video, the optical flow magnitude was averaged, and statistical features such as the mean, variance, skewness, and kurtosis were

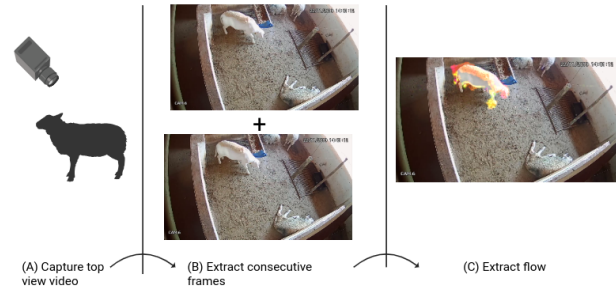


Figure 3. Optical flow extraction schema: (A) The video of each pen is recorded from a top view. (B) Two consecutive frames were taken, and the optical flow is extracted (C).

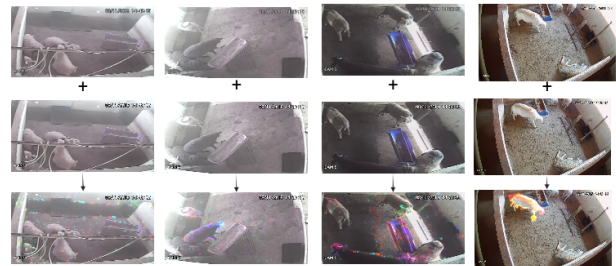


Figure 4. Optical flow extracted from each pen using two consecutive frames.

computed for each pen. The resulting optical flow data, as shown in Figure 4, were then analyzed to identify outliers, following the methodology outlined by [15, 4]. An outlier was flagged when the variance of the optical flow magnitude exceeded three times the mean variance for the corresponding hour. When outliers were detected, all four optical flow measures (mean, variance, skewness, and kurtosis) for that time period were excluded from the final analysis. These outliers typically resulted from factors such as poor video quality, insects obstructing the camera lens, or the presence of people in the video (either attending to the sheep or not). This preprocessing step ensured that only high-quality optical flow data were included in the behavioral analysis, reducing the potential for inaccuracies caused by external factors.

3.3 Statistical Analyses

The optical flow measures were correlated with sheep activity using Pearson correlation coefficients to assess the relationship between the motion data and the behavioral activity of the sheep. For this analysis, the hourly averages of the optical flow measures (mean, variance, skewness, and kurtosis) and the observed sheep behavioral activities (standing, walking, and laying) were used. The correlation was performed for each pen and for each day, resulting in a total of 64 observations (4 pens $\times$ 4 days/pen $\times$ 4 hours/day). This allowed the researchers to determine how closely the optical flow data—captured through motion analysis—aligned with the actual behavior of the sheep in terms of their activity levels, helping to identify patterns and anomalies in the behavior based on movement.

4. Results

As shown in Table 3, mean optical flow was higher in camera 3 on November 9th (6.164), in camera 4 on October 20th (5.298), in camera 5 on November 22nd (6.448) and in camera 6 on November 8th (3.288). Variance of optical flow was higher in camera 3 on November 9th (3.036), in cameras 4 and 5 on November 22nd (3.542 and 5.138, respectively) and in camera 6 on November 8th (2.514). Skewness of optical flow was higher in cameras 3 and 6 on November 22nd (0.536 and 1.192, respectively) and in cameras 4 and 5 on November 8th (0.414 and 1.508, respectively). Kurtosis of optical flow was higher in camera 3 on November 22nd (0.521), in camera 4 on October 20th (0.122), in camera 5 on November 8th (14.971) and in camera 6 on November 9th (2.257). Skewness and kurtosis were below 0.6 everyday in cameras 3 and 4 and had the highest values in camera 5 (1.508 and 14.971, respectively). Camera 6 has the lowest mean optical flow for each day, while camera 5 has the highest mean of all on November 22nd (6.448).

Table 3. Optical flow measurements for sheep on four different days in each camera.

		October		November	
		20th	8th	9th	22nd
Cam. 3	Mean	5,767	5,087	6,164	4,401
	Variance	1,961	2,243	3,036	2,910
	Skewness	0,228	0,107	0,004	0,536
	Kurtosis	0,090	0,055	-0,039	0,521
Cam. 4	Mean	5,298	4,451	4,968	4,634
	Variance	1,141	2,837	3,324	3,542
	Skewness	0,121	0,414	0,315	0,363
	Kurtosis	0,122	0,110	0,053	-0,089
Cam. 5	Mean	X	5,107	5,746	6,448
	Variance	X	3,289	3,838	5,138
	Skewness	X	1,508	1,333	0,559
	Kurtosis	X	14,971	12,366	0,678
Cam. 6	Mean	2,109	3,288	2,732	2,522
	Variance	0,612	2,514	1,618	1,754
	Skewness	0,209	1,078	1,107	1,192
	Kurtosis	1,047	1,774	2,257	2,156

As shown in Table 4, mean optical flow was higher in cameras 3 and 4 between 12:00 and 13:00 (5.568 and 4.993, respectively) and in cameras 5 and 6 between 08:00 and 09:00 (6.357 and 3.089, respectively). Variance of optical flow was higher in cameras 3 and 4 between 12:00 and 13:00 (2.712 and 3.113, respectively) and in cameras 4 and 5 between 08:00 and 09:00 (5.058 and 1.977, respectively). Skewness of optical flow was higher in cameras 3 and 6 between 10:00 and 11:00 (0.230 and 0.928, respectively), in camera 4 between 08:00 and 09:00 (0.363) and in camera 5 between 14:00 and 15:00 (1.364). Kurtosis of optical flow was higher in camera 3 between 08:00 and 09:00 (0.459), in cameras 4 and 6 between 10:00 and 11:00 (0.121 and 2.189, respectively) and in camera 5 between 14:00 and 15:00 (13.380). Skewness and kurtosis

were below 0.5 everyhour in cameras 3 and 4 and had the highest values in camera 5 (1.364 and 13.380, respectively). Camera 6 has the lowest mean optical flow for each hour, while camera 5 has the highest mean of all between 08:00 and 09:00 (6.357).

Table 4. Optical flow measurements for sheep by hour in each camera.

		Hours of day			
		08-09	10-11	12-13	14-15
Cam. 3	Mean	5,269	5,203	5,568	5,478
	Variance	2,367	2,343	2,712	2,684
	Skewness	0,299	0,230	0,148	0,188
	Kurtosis	0,459	0,099	0,000	0,050
Cam. 4	Mean	4,640	4,886	4,993	4,892
	Variance	2,320	2,554	3,113	2,680
	Skewness	0,363	0,300	0,244	0,288
	Kurtosis	0,078	0,121	-0,054	0,070
Cam. 5	Mean	6,357	5,751	5,514	5,516
	Variance	5,058	4,221	3,338	3,844
	Skewness	0,869	1,281	1,016	1,364
	Kurtosis	4,170	12,086	7,807	13,380
Cam. 6	Mean	3,089	2,487	2,410	2,547
	Variance	1,977	1,328	1,294	1,723
	Skewness	0,806	0,928	0,893	0,886
	Kurtosis	1,536	2,189	1,869	1,595

As shown in Table 5, camera 3 presented negligible correlation between any optical flow measures and sheep behavior, except skewness that presented very low negative correlation with the time spent laying (-0.215) and low negative correlation with the time spent standing (0.202). In camera 4, mean optical flow presented low positive correlation with time spent laying (0.344) and very low negative correlation with time spent standing (-0.240) and walking (-0.279). Optical flow variance presented negligible correlation with time spent laying and standing and very low negative correlation with time spent walking (-0.103). Skewness presented low negative correlation with time spent laying (-0.424), low positive correlation with time spent walking (0.357) and very low positive correlation with time spent standing (0.288). Kurtosis presented very low negative correlation with time spent laying (-0.246) and very low positive correlation with time spent standing (0.147) and walking (0.239). In camera 5, mean optical flow presented low negative correlation with time spent laying (-0.410), low positive correlation with time spent standing (0.330) and very low positive correlation with time spent walking (0.187). Optical flow variance presented low negative correlation with time spent laying (-0.480) and low positive correlation with time spent standing (0.327) and walking (0.315). Skewness and kurtosis presented negligible correlation with sheep behavior. In camera 6, mean optical flow presented moderate negative correlation with time spent laying (-0.621), low positive correlation with time spent standing (0.403) and moderate positive correlation with time spent

walking (0.501). Optical flow variance presented moderate negative correlation with time spent laying (-0.543) and low positive correlation with time spent standing (0.357) and walking (0.432). Skewness presented negligible correlation with time spent walking, very low negative correlation with time spent laying (-0.190) and very low positive correlation with time spent standing (0.183). Kurtosis presented very low positive correlation with time spent laying and very low negative correlation with time spent standing (-0.198) and walking (-0.200).

Table 5. Pearson correlation coefficients between optical flow measures and behavioral time budget in each camera

		Optical Flow Measures			
		Mean	Var	Skew	Kur
Cam. 3	Laying	0,003	-0,089	-0,215	0,023
	Standing	-0,025	0,060	0,202	-0,007
	Walking	0,044	0,088	0,099	-0,039
Cam. 4	Laying	0,344	0,057	-0,424	-0,246
	Standing	-0,240	-0,005	0,288	0,147
	Walking	-0,279	-0,103	0,357	0,239
Cam. 5	Laying	-0,410	-0,480	0,075	0,095
	Standing	0,330	0,327	-0,059	-0,045
	Walking	0,189	0,315	-0,037	-0,095
Cam. 6	Laying	-0,621	-0,543	-0,190	0,280
	Standing	0,403	0,357	0,183	-0,198
	Walking	0,503	0,432	0,054	-0,200

5. Discussion

As optical flow is the estimation of movement in a sequence of frames, the correlation between sheep behavior and mean optical flow followed expected patterns in cameras 5 and 6, where mean optical flow has negative correlation with time spent laying, low in camera 5 and moderate in camera 6, indicating that sheep laying down resulted in minimal movement. There was a low positive correlation between mean optical flow and time spent standing for both cameras, as standing involves some minor movement. For time spent walking, there was a very low positive correlation in camera 5 and a moderate positive correlation in camera 6, which reflects the increased movement when sheep were walking. In contrast, in cameras 3 and 4, sheep spent more time laying down but had higher mean optical flow, negatively affecting the correlation coefficients. This anomaly was caused by camera resolution issues and connection cable noise, which generated false motion signals in the video data.

The variance of optical flow represents changes in movement within the group. When sheep were laying down, there was minimal movement, except for rare instances when a sheep briefly got up. However, when standing, sheep could walk for a short period or cross the pen, sometimes followed by others, leading to more variability in movement. This pattern resulted in a negative correlation between variance and time spent laying, low in camera 5 and moderate in camera

6, and positively low correlation between variance and time spent standing and walking in both cameras. For cameras 3 and 4, there was no correlation between variance and time spent laying or standing, and a negligible to low negative correlation with time spent walking, particularly in camera 4.

According to [4], a highly positive skewness in optical flow indicates that the movement mode is displaced from the mean toward slower movement, while highly positive kurtosis reflects unusual movement. In their study on broiler chickens, Dawkins et al. found that flocks with healthy birds had lower skewness and kurtosis in their optical flow data compared to flocks with lame birds. The reasoning was that healthy birds walked uniformly, displaying consistent movement patterns, whereas lame birds exhibited varied degrees of difficulty in walking, resulting in mixed movement abilities within the group. This variability in movement was reflected in the higher skewness and kurtosis values for lame birds.

Applying this same principle to our sheep data, we assume that low skewness and kurtosis suggest a movement mode that is displaced closer to the mean, likely in the direction of faster movement. This could indicate more uniform and coordinated behavior within the group, with sheep moving in a more consistent manner. In contrast, if higher skewness and kurtosis were observed, it might suggest disruptions in movement or unusual patterns, potentially caused by environmental factors or health issues affecting individual animals within the group. Thus, in our context, low skewness and kurtosis would reflect normal movement patterns, while higher values could be indicative of irregular or slower movements among the sheep. In cameras 3 and 4, skewness and kurtosis were below 0.6, suggesting that constant noise was being detected as movement, even when the sheep were lying down. In camera 5, skewness and kurtosis showed no correlation with sheep behavior, but in camera 6, there was a very low correlation with sheep movement. Notably, camera 5 recorded the highest skewness (1.508) and kurtosis (14.971) on November 8th between 14:00 and 15:00, with values of 1.364 for skewness and 13.380 for kurtosis during that hour. These high values suggest the presence of unusual and slow movement, likely due to some external disturbance or abnormal activity in the sheep's environment during this time.

6. Conclusion

In this study, we proposed a behavioral analysis of sheep using optical flow measures such as mean, variance, skewness, and kurtosis. These optical flow metrics were correlated with the time spent in various activities—laying, standing, and walking—to assess movement patterns and behavioral changes. The results demonstrate that these measures can effectively reflect sheep behavior and can be used as a tool for monitoring behavioral activity changes. This approach provides a non-invasive method to track activity, identify irregularities, and enhance the welfare and management of sheep in a farm setting. Future research should focus on further developing this methodology by integrating advanced classification algo-

gorithms to automate the identification of different behaviors in sheep. By refining data processing techniques, real-time analysis can be enhanced, allowing for more efficient and immediate detection of behavioral changes. Furthermore, research should explore ways to present and transmit this information effectively to caregivers. Automated alert systems or dashboards that translate the optical flow data into actionable insights would support caregivers in making timely decisions, such as addressing health issues or environmental concerns, thereby improving the overall management of livestock.

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Author contributions

The lead author Pedro Henrique Neves da Silva developed the code and wrote the paper. Authors Rodrigo Gonçalves Mateus and Sebastião Lucas Neves de Melo were responsible for the management and care of the sheep. Authors Diego André Sant'Ana and Hemerson Pistori participated in the conception of the ideas and in the supervision and review of the papers.

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