

Unobtrusive bioanalytics for impact-related sport activities

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Abstract. A preliminary study was performed to determine the potential of an image analysis methodology to detect breathing parameters using a smart mouthguard. The smart mouthguard would be enabled with a light-emitting diode (LED) to transfer information regarding relevant breathing frequencies. The detection accuracies of Viola-Jones based algorithms were determined using a video stream of a virtual LED enabled mouthguard. A good accuracy for the detection of the LED enabled mouthguard was found and the simulated breathing frequency was correctly predicted using the proposed algorithm. The potential to measure breathing parameters using the presented smart mouthguard methodology might lead to new ways of injury prevention and performance management.

Keywords: In-body wearables · Physical Activity · Human Factors · Respiration
· Prevention · Design engineering

1 Introduction

Contact sports

As athletic participation continues to increase around the world, the need for mouthguards will continue to climb. It has been estimated that over 40 million mouthguards are sold annually in the US alone [1]. This number is expected to grow proportionally with the increase of contact sport athletes and the surge of associations that make wearing a mouthguard compulsory. There is a strong need within the contact sports community to show that these sports can be played safely, as contact sports now include some of the fastest growing sports in the world.

Breathing and injury

Research has shown that (contact) injury rate is higher towards the end of a sports match [2], indicating an obvious link with fatigue. The suggested relationship between injury and fatigue is supported by findings that the majority of rugby league injuries occur during tackles [3] and in the second half of matches [4] when players are more fatigued. The risk of injury seems to increase when contact-sport athletes fatigue during the game. Their decision making process begins to be compromised, as they get more fatigued [5]. It has been proposed that exercise tolerance in highly motivated subjects is

ultimately limited by the perception of effort [6]. This shows that muscle fatigue alone can't explain why a physical activity is consciously terminated [7]. These findings provide further support to the psychobiological model of exercise tolerance and performance. Therefore, accurate and obtrusive information of physical exertion can greatly help in injury and performance management. Physical exertion has been shown to be the primary cause for exhaustion and has a strong physiological association with breathing parameters (e.g. respiratory frequency) [6]. Changes in ventilation will also directly alter the perception of exertion, while this is not the case with other often measured physiological parameters, such as heart rate [8, 9].

The mouthguard provides the ideal system for unobtrusive tracking of these important breathing parameters. Other systems that track respiratory rate often require the athlete to wear additional devices, which often translate a low adherence to these new technologies. Chest bands are probably the most used approach to pick-up respiratory rate information, but the chest band design provides limited suitability across all contact sports athletes. The belt can easily be displaced or damaged during direct contact. It would not provide a viable option for close contact sports, such as mixed martial arts, and it might even be a safety risk if there is any chance of entanglement. The same applies to more integrated systems that might have the measurement devices embedded within the athlete's clothing [10]. Although, it does create a more discreet design approach, it cannot rely on the assumption that the fabric would only move due to respiration. Clothing is grabbed and pulled in many contact-sports, both intentionally and un-intentionally. More clinically orientated devices that can detect breathing rate using electrocardiogram (ECG) and photoplethysmogram (PPG) signals [11] provide high-quality measurements. However, these kind of technologies are not fit for purpose for application on the sports field. A more user-friendly technique would be to remotely monitor the athlete's breathing through non-contact methodologies [12]. This would deliver a very user-friendly approach, but it suffers from a limited operation range and strict environment requirements in terms generating useful results. Although, the presented "state-of-the-art" non-contact monitoring solution [12] uses frequency modulated carrier waves and localization techniques to separate different sources of motion in the environment it will be difficult to reach meaningful detection levels in real-world complex scenarios.

The ideal approach would be to use the unobtrusive nature of a (smart) mouthguard with the remote monitoring capabilities of an imaging analysis methodology. The application of feedback through image analysis is widely adopted by trainers and athletes. It has clear benefits to the user who wants to improve their technique to reduce unwanted injuries. It can also be applied by the coach, as a training tool, to create a competitive advantage [13]. Combining analytical signal processing for physiological data with an in-body tracking system that is embedded in an already well-established piece of sport gear provides a minimally obtrusive solution for monitoring purposes. An interesting way to convey information between the mouthguard and the image recording equipment would be by the use of a light emitting source. A light-emitting diode (LED) embedded in the mouthguard would provide a low-cost and low-energy solution for data transfer.

The objective of this study is to compare the mouth detection accuracy between several image analysis algorithms in order to determine which algorithm would be the most suitable for estimating breathing frequency based on a novel LED enabled smart mouthguard. The detection algorithms will be assessed using simulated data, to provide an absolute reference value for the comparison between algorithms. The most accurate detection algorithm will be used to subsequently detect the virtual light (LED enabled mouthguard) within the mouth. A final comparison will then be made between the simulated and detected breathing frequency.

2 Methods

2.1 Smart Mouthguard

The smart mouthguard consist of a circuitry that enables acoustic signals to be processed and outputted through a LED. A high brightness LED can generate a signal that can be detected even within a well-lit environment. The LED can be turned “on” or “off” in sync with the respiratory signal that is obtained by an acoustic sensor. Embedding this whole system into a mouthguard creates a potentially novel method for transferring respiratory data.

An acoustic sensor placed in the oral cavity provides a data collection technique that generates a good signal-to-noise ratio, due to its close proximity to the source of interest. It benefits from the fact that the mouth will act as insulator for external background and environmental noise. The system consists of a small lithium ion battery to power a printed circuit board that is LED enabled and connected to an acoustic sensor (Fig. 1 shows an example prototype). The LED-enabled smart mouthguard delivers a visual cue of when the participant is inhaling or exhaling (light is “on”) and the transition points between them (light is “off”).



Fig. 1. Prototype of the electronics embedded in the mouthguard.

The workings of this prototype were used to produce a stack of images that contained a simulated light source near the center of the mouth. The simulated light in the images

represents the LED within the smart mouthguard, from a virtual perspective. The images were combined to create a video stream in which the “on” and “off” timings of the LED were exactly known and allowed for a direct comparison with the outcomes of a detection algorithm.

2.2 Video stream

Data was recorded using the Facetime HD camera of an Apple Macbook Pro (Retina, 13-inch, 2013). The video stream consisted of 511 frames, which produced a video of 25 seconds. A recording was taken of a subject’s head moving sideways, up and down, as well as rotating around a longitudinal and horizontal axis. The range of motion was large ($>90^\circ$) in order to create a challenging video for the detection algorithm. The mouth was manually labelled for all frames to provide an accurate reference value for comparison between the different versions. A simulated LED was generated by placing a small light blue box in the middle of the mouth in some of the frames. The virtual LED was placed within the video stream in such a way that it would produce a simulated breathing frequency of 0.1Hz.

2.3 Image analysis

The aim of the image analysis algorithm is two-fold. The first step is to detect the location of the mouth within a frame (Fig. 2). This optimization step helps with the subsequent identification of the LED, by reducing the search area. The detection of the mouth also helps to reduce the incorrect detection of light sources that do not represent the LED-enabled mouthguard. The aim was to have the mouth accurately detected, ideally with an accuracy of $>95\%$, before the subsequent detection of the LED would be considered.

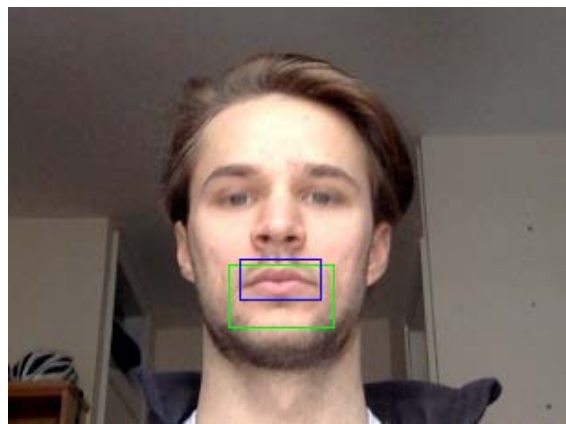


Fig. 2. A single frame of the video stream showing the manually labeled mouth (small dark blue box) and the area that was identified by a detection algorithm to contain the mouth (larger green box).

The first algorithm relied on detecting the users mouth within the frame of a video using the Viola-Jones (VJ) method [14]. This method could be implemented in real-time, which is essential for the application of the smart mouthguard. The first version (vj1.0) detects every face within each frame. Then the algorithm searches the area of each face to detect a mouth within that face. Additional versions (vj1.1-2) were designed that used the location of the mouth in the previous frame to locate the mouth in the current frame. Thus, the algorithm searches an area around the previous mouth's location. This approach should speed up the detection process, as the algorithm is searching only a fraction of the total area available. The next versions (vj1.3-4) were developed to prevent the algorithm from getting stuck on e.g. an eye. The VJ method can easily perceive an eye to be a mouth, due to their similar shape. Therefore, the code was optimized to better predict which of the features that are identified as a mouth in the VJ method is actually the mouth. The algorithm relies on the fact that the VJ method should find both eyes and the mouth, we just need a way to determine which of those found features is the actual mouth. The first technique (vj1.3) uses the fact that most often the actual mouth will be the lowest feature found in the frame, so the algorithm saves the feature lowest in the frame as the mouth. The second technique (vj1.4) uses the fact that the distance between the eyes will be shorter than the distance between the mouth and either eye. The second main version (vj2.0-1) of the algorithm does change the base set-up for the mouth detection. Instead of sending the entire video for analysis to a separate script the main script now creates a separate class for each individual frame and then performs the analysis on that frame. This should lead to an increase in time taken for the entire script to run, but it makes the algorithm more suitable to run in real time.

The third versions (vj3.0-4) implement a Kalman filter (KF) to better track the mouth within the frame. Version vj3.0 uses the actual mouth and face locations as the measurement input for the KF. This version was only implemented to ensure the KF works properly and therefore does not provide any meaningful results in terms of accuracy. The vj3.1 runs the algorithm with KF, with vj3.2 providing an additional correction to select the mouth that is located closest to the bottom of the image if multiple mouths are detected. The next version (vj3.3) uses the KF's predicted location of the mouth to determine which mouth is most likely to be the correct mouth. The last version (vj4.1) searches the area of the detected mouth for a blue LED and uses that information to more accurately predict the mouth's actual location (Fig. 3).

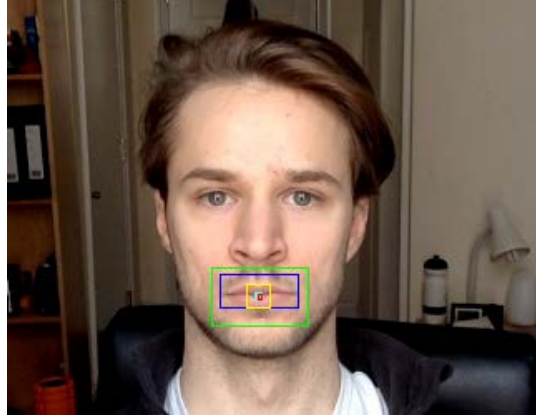


Fig. 3. A single frame of the video stream with the simulated LED (small light blue square in the middle of the mouth). It shows the manually labeled mouth (dark blue box), mouth area detected by algorithm (larger green box), manually labelled LED (yellow squared box) and detected LED (small red square box).

2.4 Simulated respiratory rate detection

The first step consisted of the detection of the light from the simulated LED. To detect the light a mask of the detected mouth is taken, using the expected colour range of the light. Then the contours of this mask are found, if there exists a contour within the mask the light is considered to be successfully detected. The mask is created by checking each pixel value inside the chosen mask is within the lower and upper colour boundaries. A digital signal is created by recording whether a light was detected / on. If the light was detected a 1 is assigned to that frame, if not then a 0 is recorded. The digital signal was further processed in order to reduce the noise in the signal.

The signal processing consisted of determining the parameters for the Kaiser window method [15] using the desired attenuation in the stop band, as well as the video sample rate. This windowing technique is used to design a suitable linear-phase filter for the signal. Then a Blackman low pass finite impulse response filter was used to filter out the high frequency components of the signal. The signal is then further processed by flooring every component of the signal below 0.5 to 0 and ceiling every component of the signal above 0.5 to 1. This generated a binary time-series signal. Finally, the signal was adjusted so that if the light was “off” for <15 frames then it was assumed that the light was lost, but “on”. The signal was corrected in this case by assigning a value of 1 for all frames identified.

2.5 Data analysis

The accuracy is determined by comparing the coordinates of the top-left and bottom-right corners of the detected object (*detected_x*) and the actual (manually recorded) object (*actual_x*). The equations 1-3 demonstrates how the score for each version is determined.

$$Score = \frac{1}{N} \sum_{i=1}^N a_i \quad (1)$$

$$a_i = \begin{cases} 0 & \text{if actual coordinate} = 0 \\ \frac{1}{4} \sum_{j=1}^4 b_j & \text{otherwise} \end{cases} \quad (2)$$

$$b_j = 1 - \frac{|detected\ x_j - actual\ x_j|}{actual\ x_j} \quad (3)$$

With N is total number of frames where the object was visible, i is the frame number, j is the indexes for the coordinates of the top-left and bottom-right corners of the desired object.

All data was processed and analyzed using Python (Python 3.6.2, Python Software Foundation, www.python.org). The algorithms were developed in Python and module OpenCV 3.3.0 was used to implement the VJ method, in addition to the python modules Numpy 1.13.1 and SciPy 0.19.1. All algorithms were implemented in the Pycharm Community Edition (www.jetbrains.com/pycharm/).

3 Results

The results for each of the algorithms described in the methods section are provided in Table 1. It can be seen that vj1.2-3 yield the lowest time per frame, while vj4.1 generates the best detection accuracy.

Table 1. The table contains data for each detection algorithm. The first column shows the different algorithms used to detect the mouth. The second column indicates the time it took to process a frame. The final column shows the detection accuracy. The vj3.0 – KF does not contain values, as it was a test version to check the KF was working correctly. *vj* = Viola-Jones and *KF* = Kalman Filter

Version	Time per frame (ms)	Detection Accuracy (%)
vj1.0	89.2	33.5
vj1.1	73.3	33.3
vj1.2	31.9	68.5
vj1.3	31.9	64.4
vj1.4	33.9	62.0
vj2.0	111.6	88.3
vj2.1	42.5	90.8
vj3.0 – KF		
vj3.1 – KF	114.6	93.5
vj3.2 – KF	47.5	87.8
vj3.3 – KF	50	89.2
vj4.1 – KF	45.8	95.9

The accuracy of the algorithm (vj4.1) for detecting the light was 79.1%. The signal processing predicted a breathing frequency of 0.125Hz, as the original simulated breathing frequency was set at 0.1Hz.

4 Discussion

The results show that a high accuracy can be achieved using a Viola-Jones (VJ) method combined with a Kalman filter alongside basic signal processing techniques to detect the mouth and virtual LED. The best performing algorithm (vj4.1) correctly determines the simulated breathing frequency. These outcomes are promising and provide a new way to assess physical performance.

Unlike pedometer and accelerometer devices this smart mouthguard makes direct physiological system measurements to determine the perceived intensity of physical performance. In addition, breathing monitoring is perfect to measure recovery and provide an estimate of overall fitness. Respiratory markers can also be used to inform the sporting community regarding training intensity and risks. The metrics can aid contact sport athletes in understanding their performance and assist in personalizing their training regime without the requirement to wear any additional gear. It can also be used to make decisions regarding the potential injury risk athletes face during training or competition. Breathing parameters can be used to measure changes in perceived exertion allowing the athlete to monitor and check how they train or play the game. It was shown that rugby league players with low speed and maximal aerobic power are at an increased risk of injury [16]. This highlights the need to look not just at impact, but also physiological performance.

The integration of the LED into the mouthguard provides a low-cost and low-energy solution for detection. Depending on the specification of the light source (e.g. brightness) and camera (e.g. focus, sample frequency and resolution), different levels of detection can be obtained on the sports field. The image analysis technique is further affected by the requirement of an unobstructed view. However, the reduction of cost and the ever-increasing quality of cameras has led to the pervasive nature of image capture. Most wearable electronic devices, such as smart phones, already come with a high-spec camera. These devices can easily be leveraged to perform the required image analysis within the sporting arena. More professional settings will have dedicated cameras that can be utilized for this purpose. An array of LEDs can be integrated to optimize detection rate at different view angles and apertures of the mouth.

This principal function of the mouthguard to prevent injury of the teeth should not be impeded by the integration of electronics. Mechanical testing needs to be performed to provide information on how the electronics can be safely integrated into such a system without increasing the risk of damage to the athlete.

The presented work in this study is based on a relative small data set, which limits the external validity of the results. The video was recorded with the head moving in many

directions, but it does not capture all the complexities of a field recording. However, these initial results show that the approach described could provide a potential viable way of detecting respiratory rate on the sports field. Further work will consist of validating the approach during field measurements and will also include the quantification of amplitude in addition to breathing frequency.

Currently, no product exists for the contact-sport market that allows for reliable and comfortable performance measurements and which can greatly increase safe participation of athletes in a wide range of sports without the need for recalibration. The smart mouthguard makes direct physiological system measurements to determine the perceived intensity of exercise. The potential promise to prevent injuries and promote safe (contact) participation will have a positive benefit on the lifelong health of those participating in these sports.

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