USABILITY ASSESSMENT OF FACIAL TRACKING FOR USE IN CLINICAL OUTCOMES AND APPLICATIONS

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ABSTRACT

There is an ever-growing body of facial tracking assessment applications available within the health and wellness sector. One of the most prominent areas is the use of 3D cameras and processing technologies in the development of rehabilitation interventions and in the measurement of health outcomes. Recent advancements in facial tracking applications within mobile platforms and cloud computing analytics suggests that new clinical assessment and human computer assessment technologies have significant future potential for pervasive in-clinic and field-based health assessment solutions. This paper reviews the technical capabilities of three facial tracking platforms with a focus on the common issues relating to clinical measurement considerations required for patient-facing systems. Key factors are assessed in relation to 3D camera platforms, mobile applications and cloud computing applications including camera position, lighting and shadows, eye detection and common obstructions or features that affect tracking. Published examples of facial tracking clinical and health wellness applications are presented in relation to human computer interaction interfaces. This paper aims to demonstrate the potential for future applications being developed relating to each of these technologies for clinic-based applications.

KEYWORDS

3D Camera Tracking, Clinical Outcomes, Clinical Endpoints, Cloud Computing Facial Analytics, Facial Tracking, Mobile Applications

1. INTRODUCTION

Facial tracking assessment applications are becoming increasingly prominent within the clinical and health and wellness sector. Human computing interfaces and patient facing systems are two areas where systems have been developed to assess the health status of a patient or provide a method of rehabilitation. There are many examples of systems within the health and wellness sector that focus on the measurement of gait and balance, upper extremity movement, chest wall motion, etc., however all these solutions rely upon robust and validated methodologies to measure health status and track changes in status over time. This paper explores the key issues associated with accurate facial tracking and assessment within the clinical assessment sector.

An ever-increasing number of 3D camera-based technologies available in today's market enables applications within 3D scanning, motion capture, gaming, wellbeing applications or clinical and healthcare research to be created. The rapid development of 3D cameras and processing technologies has resulted in a market with numerous options, all with varying strengths and weaknesses. Within facial tracking and analytics, recent advancements in mobile platforms and cloud computing applications provide new and innovate alternative solutions that can be applied to the clinical assessment of patients within human computing interfaces and patient-facing systems.

1.1 Facial Tracking Application to Clinical Research

Facial tracking may provide the opportunity to learn more about the status, progression and treatment of certain disease indications, in particular those affecting the central nervous system (CNS). There are a number of attributes that might be possible to measure using facial tracking technologies that may provide opportunities for novel objective clinical outcome measures, these include expression detection, facial symmetry and movement, blink detection and eye tracking, facial muscle strength and tongue dexterity.

1.1.1 Expression Detection

The relative positioning of facial landmarks enables the determination of expression. Conditions such as autism are developmental disorders associated with impairments in social interaction. A source of those impairments is difficulty creating facial expressions of emotion. In young children, autism is difficult and time consuming to diagnose by healthcare professionals. Researchers at Duke Medicine have developed an app-based solution to identify a child's facial expression using video captured using the front-facing camera while watching short video clips designed to generate an emotion such as laughter or surprise (Autism and Beyond, 2014).

1.1.2 Facial Symmetry

Facial paralysis is a common component of conditions such as stroke and Bell's palsy, which can improve through regular conduct of exercise regimens. Longitudinal changes in aspects of facial paralysis in these conditions could be tracked by measuring aspects of facial symmetry and distortion based on relative distances between specific facial landmarks. Numeric measures of facial symmetry enable the tracking of temporal improvements arising from pharmacological or physical therapy treatment.

1.1.3 Blink Detection and Eye Tracking

Identifying eye opening and closure events may facilitate the measurement of blink rate. Blink rates are believed to reflect the activity of the central dopaminergic systems (Karson, 1983). Patients with Huntingdon's disease or schizophrenia show higher blink rates than normal subjects; patients with Parkinson's disease and progressive supranuclear palsy show lower blink rates (Grandas et al, 1994). Understanding the scan patterns associated with eye movements can be useful in the study of certain neurological diseases and brain injury. Altered fixation stability and saccadic movements (rapid eye movements that abruptly change the point of fixation) are associated with several CNS disorders such as Huntington's disease, progressive supranuclear palsy and Parkinson's disease (Termsarasab et al, 2015). In the early stages of dementia, saccadic eye movement recordings may help discriminate between different types of the disease (Mosimann et al, 2005). Eye tracking is also gaining increased interest as a potential biomarker for brain injury (Samadami, 2016).

1.1.4 Facial Muscle Strength

Facioscapulohumeral muscular dystrophy may present as a weakness of the facial muscles. For example, a patient's eyes may remain slightly open when asleep, or they may be unable to tightly close their eyes. Patients may also experience difficulty pursing their lips. Using the tracking points around the mouth and lips it may be possible to use facial tracking technology to instrument a lip pursing test, along with other tests of facial muscle strength, which could provide valuable outcome measures in these and other disease indications.

1.1.5 Tongue Dexterity/Agility

Patients with Huntingdon's Disease are often assessed using the Unified Huntington's Disease Rating Scale (Kieburtz et al, 2001), an assessment conducted and rated by clinicians. One component of the assessment considers measurement of aspects of motor impersistence, specifically difficulty keeping the tongue fully protruded upon command. The scale's tongue protrusion task is performed by asking the patient to hold the tongue extended for 10 seconds and rating the response on a 5-point verbal response scale. Facial tracking approaches may enable instrumentation of tests such as these, with increased precision of measurement and greater richness of information collected.

2. CAPABILITIES OF FACIAL TRACKING

Facial tracking technological solutions are becoming more common within the healthcare sector. The most common hardware utilised to track the face and its movements are 3D Depth cameras using inbuilt infrared LED's to illuminate the subject. Background objects can be ignored as the computer can accurately isolate individual objects based upon their detected distance from the camera. Accurate 3D tracking of facial landmarks enables the tracking and measurement of many aspects of facial movement such as facial paralysis recovery after stroke/Bell's palsy. Camera tracking has been utilised for many years, however this has often focused on 2D camera tracking due its low setup costs. 2D camera tracking uses contrasting colours to pick out facial features in normal lighting conditions. However, lighting conditions and skin tone can dramatically affect the results when there are significant contrast changes, however Raja et al (1998) and Kjeldsen and Kender (1996) discuss segmentation approaches to overcome these issues. Background colours can also affect the ability for the camera to track features as the objects in the picture merge into one another. Variable lighting conditions can adversely affect the quality of tracking and can affect the accurate tracking of facial landmarks; this has been especially noted with the Microsoft Kinect (Shires et al, 2013). 2D depth tracking has severe limitations with expression recognition. Table 1 provides a brief comparative analysis of the advantages and disadvantages of 2D v 3D depth camera facial tracking.

Table 1. 2D vs 3D Camera Solutions - Facial Tracking Comparative Assessment

2D Facial Tracking Advantages	3D Facial Tracking Advantages
– Lower Bandwidth Requirements.	– Three Dimensional Measurements.
– Lower Cost (Hardware).	– Unaffected by head orientation.
– No Specialised Hardware Required.	– High accuracy/ increased range of depth data.
	– Increased accuracy of pose recovery.
	– Fast and accurate facial feature ID and tracking.
	– High detection rate and sampling rates.
	– Accurate expression recognition.
2D Facial Tracking Disadvantages	**3D Facial Tracking Disadvantages**
– Limited by lighting levels.	– Increased setup costs (hardware and software).
– Limited by occlusions.	– Complexity of programming.
– Image processing limitations.	– Increase in initial calibration complexity.
– CPU intensive for reduced outputs.	– Restrictions can exist with lighting levels.
– Limited emotion tracking capabilities.	– Some limitations by occlusions.
– Limited facial feature tracking & identification.	– Unknown response to facial feature deformities.
– Limited expression recognition.	– Some limitations for facial feature detection.
– Limited by scene clutter.	– Minor limitations caused by laser refraction during tracking.
– Limited by skin tone.	

Recent advancements in facial tracking technologies suggests there are three key areas where they will be utilised within the clinical and healthcare sector. The current state of the art focuses on 3D camera tracking modules; however, a rapidly developing area focuses on mobile platforms, such as the Apple© iPhoneX® that utilises Face ID which is described as an intuitive and secure authentication method enabled by a state-of-the-art TrueDepth camera system (Apple Inc., 2017). Visage Technologies© (Linköping, Sweden) also offer FaceTrack, FaceAnalysis and FaceRecognition packages (Visage Technologies, 2018).

Cloud-computing data analytics focusing on facial tracking applications also provides a solution with significant future potential. Vinay et al (2015) demonstrates innovation with a cloud based big data analytics framework for face recognition in social networks using machine learning and Hossain and Muhammad (2015) present a cloud-assisted speech and face recognition framework for health monitoring.

2.1 3D Camera Tracking Modules

3D Camera modules are computer add on devices; the two best known are the Microsoft Kinect and Intel RealSense camera ranges. These camera modules use 3D depth camera technology paired with a RGB & IR camera. Signals from these are combined and passed into a tracking algorithm to identify objects within a captured image. Both the Intel RealSense and Microsoft Kinect camera ranges utilise freely available SDKs (Software Development Kits) that allow third party developers to build upon existing libraries developed by the manufacturers. Table 2 presents the advantages and disadvantages associated with 3D camera modules.

Table 2. 3D Camera Modules Advantages & Disadvantages

Advantages	Disadvantages
– Fast and reliable tracking is achievable.	– Limited to selected device/manufacturers.
– Camera modules can be positioned as required.	– Additional hardware required (PC/Screen).
– SDK's are typically free to download.	– Camera modules are often bulky.
– High resolution	– Some SDK's do require a licence fee which can be quite expensive.
– Fast processing of live camera frames.	

3D Camera modules require additional hardware such as a PC/workstation and visual display. The camera modules are relatively cheap (~US $270), however the additional hardware significantly raises the costs. The 3D camera modules tracking quality excels due to the high-resolution colour cameras and the use of depth camera technology to extract faces from a photo frame. The camera can be positioned as required to capture the targets face from any desired angle within the camera's field of view (FOV).

Table 3 provides a brief overview of the technical capabilities of the Microsoft Kinect 2.0 (Microsoft Corp., Redmond, Washington, USA), the Intel® RealSense™ SR300 and D435 (Intel Corp., Santa Clara, CA, USA) and the CREATIVE® BlasterX SENZ3D (Creative Technology Ltd., Jurong East, Singapore). The Microsoft Kinect Sensor V2/2.0 has however ceased manufacture potentially signalling the end of Microsoft's involvement in this sector (Good OS, 2017). The Intel RealSense camera range is best placed to take advantage in the clinical and healthcare sector (Siena et al, 2018); RealSense technology is utilised in many other camera modules including the CREATIVE® SENZE3D.

Table 3. Comparison Of 3D Camera Tracking Modules

Specification/Function	Intel® RealSense™ SR300	Intel® RealSense™ D435	Microsoft Kinect® 2.0	CREATIVE® BlasterX SENZ3D
RGB Camera (Pixel)	1080 at 30 FPS, 720 at 60 FPS	1920 x 1080 at 30 FPS	1920×1080 at 30 FPS	720p at 60 FPS, 1080p at 30 FPS
Depth Camera (Pixel)	Up to 640 x 480 at 60 FPS	Up to 1280 x 720 at 90 FPS	512×424 at 30 FPS	Up to 640 x 480 at 60 FPS
Range (m)	0.2-2	0.11 - 10	0.7-6	0.2-1.5
Facial Tracking & Recognition	Yes	Yes	Yes	Yes
Facial Tracking Points *	78	78	87	78
Expression Recognition	Yes	Yes	Yes	Yes
Connectivity (USB)	3.0	3.0	3.0	3.0
Release Date	Q1 2016	Q1 2018	Q4 2013	Q4 2016
Approximate Price (US$)**	80	180	30	270

* SDK Version Dependant ** Prices as of March 2018

2.2 Mobile Based Camera Tracking

Mobile application SDK's utilise the existing cameras on mobile platforms. The application developer captures an image from the mobile device and passes it into a tracking SDK. If a face is detected, the SDK outputs face coordinates and landmark points of key facial features. Mobile application SDK's often utilise a software licensing system, either on a number of devices using the SDK or licences per developer working on the solution. It is often the case that a separate licence is required for each platform being targeted (IOS/Android). This can prove to be costly and requires payment throughout the lifetime of the product. Table 4 presents key advantages and disadvantages associated with mobile camera tracking solutions.

Table 4. Mobile Based Camera Tracking Advantages & Disadvantages

Advantages	Disadvantages
– Integrated into existing products owned by patients	– Offset camera will affect results. Camera may not sit centre to the screen.
– Fast processing of live camera frames	– Support for multiple devices required in solution (Camera resolutions/Quality)
– Platform is designed for mobility	– Speed is dependent on device specifications
	– SDKs and licensing can be expensive
	– Cross platform development needed to support all common devices (IOS/Android)
	– Poor or excessive lighting can cause issues

2.3 Cloud Computing Facial Tracking

Cloud computing facial tracking uses a web API system to process an image on a web server; the web server runs the facial tracking algorithms on the image and returns the results in either an XML or JSON format. The results contain a set of coordinates for each face located along with landmark points for each. The system requires access to the internet as all cloud-based solutions are hosted on the World Wide Web (WWW). The speed of the call is dependent on the connection speed and the latency of the connection. Cloud computing solutions are not suitable for video streams due to the latency, they are however capable of providing results to any device capable of connecting to the WWW.

Cloud computing solutions are very reliable and are often linked to artificial intelligence (AI) systems that continuously improve their algorithms to improve accuracy. Cloud computing solutions are priced on the number of calls to the API; many services offer a free level of access for low volume calls. Cloud computing offers a reliable system which has low implementation and setup costs due to API implementation which can take hours not days/weeks/months, unlike other solutions. With variable pricing which adapts to usage, this provides a low-cost solution accessible from any platform and can use any camera, mobile, web or photograph. However, drawbacks include slow frame-by-frame processing rates over the Internet and incompatibility with live video.

3. PERFORMANCE ASSESSMENT OF FACIAL TRACKING

Facial tracking performance was assessed utilising a 3D camera-tracking module (Intel RealSense), cloud computing (FacePlusPlus) and a mobile platform (Visage Technologies). Through assessment, key considerations have been identified that will be important when developing future clinical applications. The use of glasses, positioning of the camera, lighting conditions and the lighting position around the target subject can all have a considerable effect on the ability for any tracking system to detect key facial features accurately.

3.1 Glasses

Glasses can present many issues with facial tracking systems. The first common issue is with the frames of the glasses being indistinguishable from the subject's face and therefore being tracked by the system as an area of interest such as the eyebrows or the eyes themselves. The second issue is with the frames or lenses of the glasses obstructing important facial features such as the eyebrows or eyes. If the feature is not visible, then the facial tracking system will estimate the position of the landmark points based upon the known features currently successfully being tracked. The third is the magnification of the eyes. Strong lenses in glasses will magnify the eye of the subject and increase the size of the eye relative to the rest of the face (Figure 1).

Figure 1. Glasses Amplifying the Eye. (Left - Visage Mobile Tracking, Right – FacePlusPlus Cloud)

3.2 Shadows

Shadows can play a significant role in altering the accuracy of the facial tracking algorithms and will alter areas of contrast and obstruct the facial tracking systems ability to track facial features. Shadows created by a pair of glasses for example can cause algorithms to track the incorrect region of the face. The landmarks highlighted on Figure 2, show the tracking algorithm has incorrectly identified the frame, shadow of the frame or reflections within the frame as eyebrow landmarks. To avoid these issues, uniform lighting is advised to be applied across the subject's face, preferably with the light source in front of the subject to prevent shadows from forming around the eye sockets, nose and lips. This will also remove shadows created by the frames of glasses.

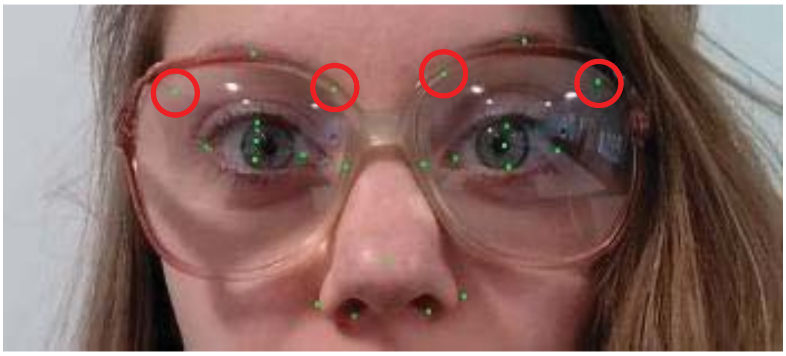

Figure 2. Inaccurate Eyebrow Tracking – Glasses & Shadows

3.3 Iris

Current eye tracking algorithms suffer from incorrect identification of the iris at the bottom of the subject's eye. This is very noticeable should the subject be performing a rehabilitative exercise that aims at widening the eyes, thereby revealing the lower white portion of the eye. Incorrect identification is also noticeable when the patient is required to look up and above the camera. On FacePlusPlus, this tracks as the bottom of the eye (Figure 3. Left) and on the Intel RealSense camera the bottom of the iris is tracked as the centre of the iris (Figure 3. Right). If accurate tracking of the eye is required, it is advised the activity does not require the subject to look away from the camera and that the focus point remains in a fixed location throughout the activity.

Figure 3. Iris Tracking (Left – FacePlusPlus Cloud Processing, Right – Intel RealSesnse)

3.4 Camera Positioning

The position of the camera relative to the desired user focus point can have an adverse impact on measurements, especially if high accuracy measurements are required. If the camera is located to the left or right of the centre then the user will visibly appear to look away from the camera, this will affect horizontal measurements as the user's face will be rotated slightly off-centre. If the camera is located above or below the focus point, this will cause the user to rotate their head up or down, thus vertical measurements will be affected. This can also affect measurements of the eyes due to the iris interfering with the tracking. This is especially important to consider when using mobile platforms (i.e. smartphones/tablets) or other hand-held devices. Different devices will place the camera in various locations in relation to the centre of the user interface (Figure 4).

Figure 4. Camera Location of Three Mobile Platforms

3.5 Lighting

Lighting can have a substantial impact on facial tracking. It affects the contrast of the subject's face in the image data being assessed. Facial tracking algorithms often use this contrast to identify regions of interest and to find the lines that make up the outline of the facial tracking feature. If the line cannot be distinguished, then the tracking either will fail or will track to the first line it can locate. Figure 5 shows FacePlusPlus tracking the same face in three different lighting conditions.

Figure 5. Normal Lighting (Left), Lighting Above (Centre), Poor/Low Lighting (Right)

The tracking in the centre and right images is enhanced by the prediction algorithms within the tracking libraries to compensate for the low lighting. This is good for functionality, as this does not require a high level of accuracy; however, it is important to note that this can have an impact when performing measurements requiring high precision. It is advised that the subject be in a well-lit area with uniform light across the face. Some landmarks within the eyes, eyebrows and lips can be slightly altered by the low contrast in the images; this will have an adverse effect on any accurate measurements made.

4. PUBLISHED FACIAL TRACKING CLINICAL APPLICATIONS

The Face to Face solution (Breedon et al, 2014), funded by the UK NIHR Invention for Innovation Programme, is a rehabilitation system for facial paralysis in stroke patients. It recognizes facial expressions by tracking movement across the face, applying the recognized motion onto an onscreen representation of the user using the Microsoft Kinect. The user performs a series of facial exercises assessed by the system and scored according to how well the user can undertake each of the defined set of expressions. This will enable shorter consultations through the presentation of quantified improvement, in addition to optimizing the performance of the exercises. Numeric measures of facial expression and symmetry enable the tracking of temporal improvements arising from pharmacological or physical therapy treatment. Other researchers have also explored methodological aspects of using depth images provided by Microsoft Kinect to accurately recognise specific facial exercises performed in rehabilitation for patients suffering from dysfunction of facial movements (Lanz et al, 2013).

González-Ortega et al (2014), produced a system to track and monitor cognitive rehabilitation exercises performed by patients suffering from left-right confusion, a cognitive condition in which subjects are unable to name or point to the right or left sides of objects, including their own body. This condition is seen in Gerstmann's syndrome (Lebrun, 2005), and can be observed in some dementia patients (Fischer et al, 1990). This system combined skeletal and facial tracking using the Microsoft Kinect in the assessment of various exercises such as touching the right eye with the left hand, touching the nose with the right hand, and touching the left ear with the right hand etc. The system was able to identify and record when the subject was able to perform each requested movement correctly, along with reaction times and movement completion times. This may aid the monitoring of longitudinal change in left-right confusion.

Youssef et al (2013) used the Microsoft Kinect system to classify six facial expressions and a neutral expression, with moderately successful results. They identified that a possible application of the work would be to help children with autism to recognize emotions and suggested that expression recognition combined with a computer animation may provide an engaging feedback and training tool. Tang et al (2017), used the Intel RealSense camera to detect emotional response to cartoon clips to assess spontaneous emotion production in children with autism.

The Microsoft Kinect has been used to detect heart rate by detecting changes in colour intensity of the facial skin due to blood flow movement resulting from heart beats. This approach has been shown to produce favourable results (Gambi et al, 2017). Other researchers have used facial tracking using depth cameras to explore fatigue detection (Anggraini et al, 2016), and tracking of articulatory movements during speech and non-speech tasks that could aid the assessment, diagnosis and treatment of motor speech disorders such as amyotrophic lateral sclerosis, Parkinson's disease (PD) and stroke (Bandini et al, 2017).

5. CONCLUSION

This assessment of facial tracking approaches has highlighted several issues that need to be considered when developing clinical applications and solutions. By careful monitoring of the user interface (UI), many of the problems with iris tracking and camera location can be avoided or minimised. Careful monitoring of the environment around the subject should also be carefully considered to prevent interference from changing light conditions and shadows; this will ensure accurate and consistent results across multiple sessions and subjects.

The selection of the optimal facial tracking platform between the three types discussed in the paper inevitably relates to factors including the availability of hardware, the price of the final product solution and the requirement for video or static tracking of facial features. Each platform offers its own advantages and disadvantages that will ultimately guide the development and the design of the product. If all these factors are taken into consideration, facial tracking can offer a solid and reliable solution for use within clinical applications.

Caution is however advised if a clinical application requires a high level of accuracy, especially when considering factors such as tremor detection. Simply based on the applications discussed within this paper alone, continued development of facial tracking algorithms, improvements in accuracy and the speed of calculations suggests there is a strong case for developing further clinical solutions including rehabilitative patient facing systems.

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