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PERSONAL AND ENVIRONMENTAL FATIGUE INSIGHTS FOR AN ONLINE COLLABORATION SERVICE

Keith Griffin

Will Reed

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AUTHORS:
Keith Griffin
Will Reed

ABSTRACT

Fatigue and burnout have become problems that are associated with remote and hybrid work. Those problems are driven by a number of factors including, for example, isolation, long working hours, cross-time zone work replacing in-person travel, sustained effort without a break, and a lack of a suitable home working environment. To address the challenge that was described above, various solutions are provided herein through several techniques. A first technique involves a personal relative video fatigue degradation monitor which measures the onset of fatigue over a given time period. A second technique involves a system that provides insights to reduce fatigue based on environmental sensor input for an online collaboration service.

DETAILED DESCRIPTION

As an initial matter, it will be helpful to confirm the meaning of an element of nomenclature. The discussion below makes reference to an online communication and collaboration service. Such a service, which for simplicity of exposition may be referred to herein as a collaboration service, brings together different capabilities such as video conferencing, online meetings, screen sharing, webinars, Web conferencing, and calling.

Fatigue and burnout have become problems that are associated with remote and hybrid work. Those problems are driven by a number of factors. Various of the contributing factors may include isolation, long working hours, cross-time zone work replacing in-person travel, and sustained effort without a break.

Some of the attempts that have been made to address the above-described problems have employed snapshot solutions that are often associated with sentiment analysis. However, one single method does not provide a true reading of how tired a person is or how they feel (in the case of sentiment analysis systems).

Sentiment analysis (as referenced above) is a known body of work, although it often only focuses on snapshot analysis. For example, one frame of video that shows a user smiling may be equated to happiness. Accordingly, such an approach produces flawed measurements.

Additionally, fatigue analysis systems exist in automotive and machinery roles to alert a driver or operator that they may be tired. Such systems employ techniques such as head detection, head roll, and drop in posture. However, they are, again, snapshots and can lead to false positives.

Another attempt at addressing the above-described problems employs measuring the distance of facial landmarks. While distance measurement can be effective in one-off situations, it can also be flawed. For example, a frown or a squint may have the same distance result on the eyes as fatigue, yielding a false positive.

In addition to the factors that were described above, a further contributing factor may include a lack of a suitable home working environment. For example, even if sufficient space is provided some home offices may suffer from a lack of adequate air circulation and light.

Some collaboration services offer various sensors that are capable of measuring environmental factors. Such factors may include air quality (using, for example, a five point scale), temperature (where a temperature of between 21 to 25 degrees Celsius is deemed to be productive), humidity (where levels between 40% and 60% are recommended), noise levels (where recommendations are for no more than 35 adjusted decibels (dBA) in a conference room setting), acoustics (where recommendations call for no more than 0.6 seconds of reverberation time in a conference room), and presence and people counts. While sensor data is very useful for a number of purposes, by itself it is just data.

Some of the existing fatigue analysis systems in automotive and machinery roles employ techniques such as head detection, head roll and drop in posture. Importantly, they do not take into consideration office environmental factors. One attempt at addressing the above-described problems employs biometric sensors and telemetry, emotion and sentiment, and mobile or vehicle sensors in a predominantly automotive setting. It may be anticipated that that different environmental inputs and factors influence collaboration and meeting users.

To address the types of challenges that were described above, various solutions are provided herein through several techniques. Each of those techniques will be briefly introduced below and then described in detail later in the instant narrative.

A first technique involves a relative fatigue analysis that can be performed over a given time period using the texture of facial features. Aspects of the first presented technique involve measuring the degradation of a person in terms of tiredness over a period of time (e.g., one working day). For example, individuals can relate to not looking or feeling as fresh, or feeling as engaged, during a late-night meeting following a full day of work as one would be earlier in the day. According to the first technique, such a condition may be inferred from the textural features of a face that are detectable using the new machine learning (ML)-based video models that are available within a collaboration service.

Aspects of the first technique may be applied within a contact center for agent engagement, which is a high-value area for collaboration. Further use cases for aspects of the first technique may encompass a security camera for workplace fatigue along with the potential for in-meeting and in-vehicle use cases that are of interest to an automobile manufacturer. In a vehicle use case, the first technique may be restricted to in-meeting fatigue as opposed to overall driver fatigue.

A second technique involves using data that is available from environmental sensors as contributions to an overall measure and resulting insight. While sensor data is very useful for several purposes, by itself it is just data. Aspects of the second technique combine such sensor datapoints with camera intelligence in order to determine the relative impact of fatigue on users.

Turning to the first technique, facial features (including the textural areas under the eyes and the lines in a forehead) can be used to determine the onset of fatigue in a given person over a period of time using data that is available from the ML-based video models that may be found within a collaboration service. Figure 1, below, presents elements of a screenshot (that shows a video mesh overlay on the face of a user) that is possible according to aspects of the first technique.

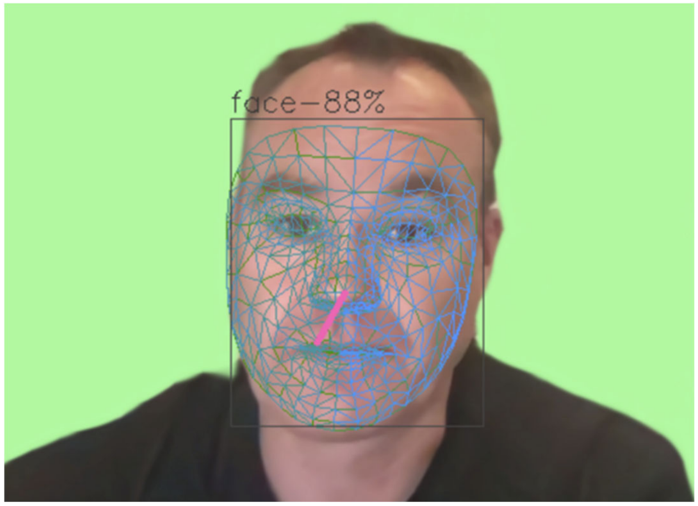

Figure 1: Illustrative Video Mesh Overlay

Aspects of the first technique measure a combination of known areas (such as any "bags" that may be found under a user's eyes) that may change as a working day progresses, to measure the onset of fatigue. Figure 2, below, illustrates an example of such an approach.

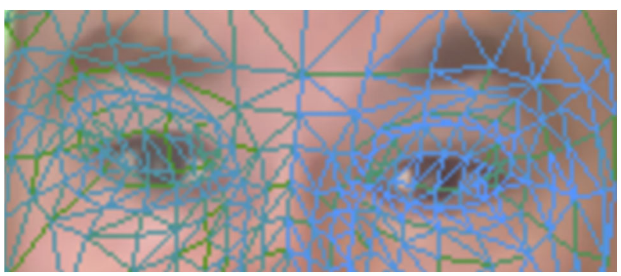

Figure 2: Exemplary User Eye Measurements

The relative change in features may be measured over a given period of time and then compared to associated thresholds to report to a user that they may be fatigued. Given the sensitivity of the data, under the first technique a resulting report may be delivered in a manner that is similar to personal insights, which is private information that is intended only for the individual.

Aspects of the first techniques support two different methods of addressing the problems that were described above. A first method encompasses a Keypoint-based technique. Under this method, a model may be trained using regression on labeled data that depicts tiredness scores on, for example, a scale of 1 to 10. Next, Keypoints may be taken from a live image (as shown in Figures 1 and 2, above). Then, regions that are known to be associated with fatigue (such as the area under the eyes (i.e., a polygon of areas under the eyes)) may be masked. The mask may then be passed through a trained model in a convolutional neural network (CNN) to identify texture fatigue effects in each region. Finally, the obtained results may be compared to previous timeline images to measure either degradation or improvement in a given timeframe. It is important to note that under an alternative starting point to the above-described method, a user may elect to provide baseline images of when they are tired and when they are not tired. Such an alternative approach is not required, but it may assist with accuracy.

A second method encompasses a tiredness comparison technique. Under this method, a model may be trained on pairs of tired and not tired images using a Siamese network technique. Similar tired image pairs may be used to train two CNN models resulting in an encoded output. Next, a Euclidean distance or a cosine similarity may be used to minimize the distance between tired images and increase the distance to known not-tired images in the output. Finally, a mask from a live image may be passed through the resulting model to determine tiredness.

An advantage of the second method is that it may accept a full-face input (as opposed to just regions) to determine tiredness. Additionally, the second method may also take into account other tiredness-related factors that may be associated with a "disheveled" look.

It is important to note that the two different methods that were described above may also be used together for increased accuracy.

The goal of the first technique is to measure fatigue degradation over time but depending upon the chosen timeline the above-described methods may also be used to determine fatigue improvement. For example, in a given day a user may have a very early meeting (at, for example, 1:00 a.m.) that is followed by sleep that is then followed by a long day. In such a case, the system would show a fatigued start followed by improvement followed by fatigue degradation. Under the first technique, the selection of a timeline is a feature consideration through which the identification of both degradation and improvement is possible. Additionally, the identification of degradation and an improvement relative to a provided baseline are also possible.

The first technique may also be considered from a multimodal approach, which may include combining similar fatigue-related measures from voice and audio streams into the output for a more rounded result.

In general, the relative and time-based measure that is provided through the first technique is more representative and valuable to a user than existing snapshot types of systems.

Turning to the second technique, the second technique leverages elements of the first technique (as described and illustrated above) in order to measure the relative impact of fatigue over time. Under the second technique, the video mesh approach that was described above in connection with the first technique may be employed. Figure 3, below, depicts elements of an illustrative screenshot that shows a video mesh overlay on the face of a user according to aspects of the first technique.

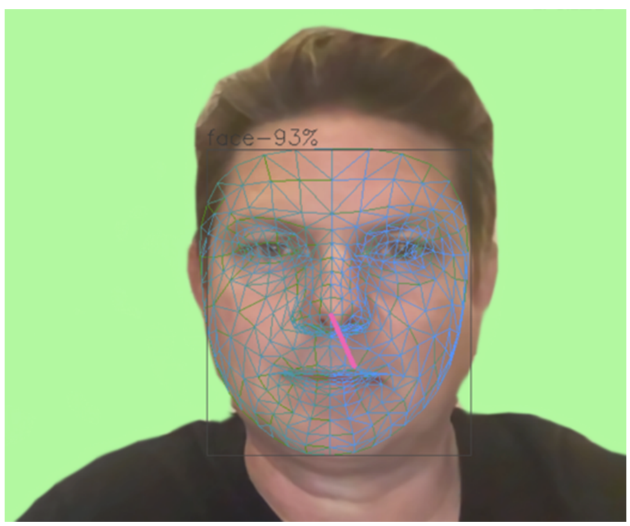

Figure 3: Illustrative Video Mesh Overlay

Next, measurements of the related environmental inputs that originate from a user's collaboration device may be collected. Figure 4, below, presents elements of a sample humidity sensor output which may be employed.

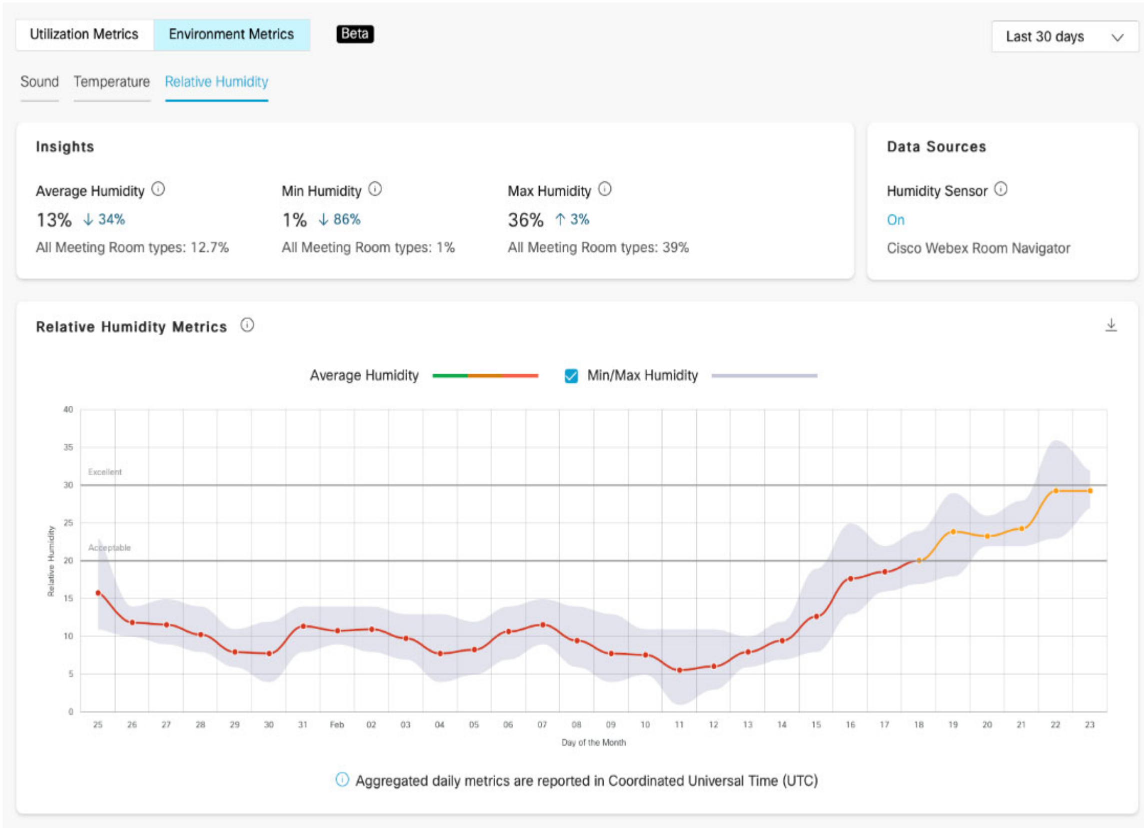

Figure 4: Sensors and Analytics in Collaboration Service Control Hub

A collaboration service control desk and room endpoints may provide sensor data for a number of factors. Such factors may include air quality (e.g., the relative air quality measuring volatile organic compounds through a Total Volatile Organic Compound (TVOC) sensor), temperature, noise, acoustics, and presence and people counts.

Many of these factors are known to influence productivity (as described above) and well-defined ranges and standards exist (also described above). The availability of such standards and reference ranges makes it quite achievable and very practical to combine a fatigue measure with the known reference ranges to determine the effect of a working environment on a user's fatigue level.

Such an approach enables a number of potential downstream use cases. Several of those use cases encompass personal insights – e.g., providing users with an indication of fatigue degradation relative to their environmental conditions, providing users with an indication of fatigue degradation for different work environments (such as a home office versus a business' office), and providing users with insights regarding modifications that may be made to different environmental conditions for optimal productivity and fatigue reduction. Other of the use cases encompass organizational insights – e.g., aggregate insights (which respect data privacy) that provide an organizational snapshot of remote working environments. Still other of the use cases encompass environmental and sustainability insights – e.g., energy and cost saving insights that are based on an optimal productive environment. Further, various of the use cases encompass predictive productivity and fatigue avoidance – e.g., providing an indication of environmental adaption that may be taken to avoid predicted fatigue.

Under the second technique, the different environmental datapoints combined with relative fatigue measurements for a user will enable a number of downstream features ranging from personal insights to the user to readout data to help the user improve their environment combined with ongoing measurement and improvement.

Using the face fatigue approach from the first technique (as described and illustrated above), the second technique takes ongoing fatigue measurements on behalf of a user. While other fatigue measurement techniques may be applicable, the approach that is described herein supports the ability to take a full face and head measurement using the new ML-based video architecture that is, for example, available within a collaboration service. This technique includes measuring areas that are known to indicate fatigue such as the texture of the area under the eyes as shown in Figure 5, below.

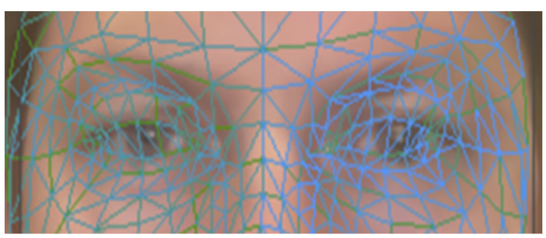

Figure 5: Exemplary User Eye Measurements

Additionally, the second technique may also consider other indicators of fatigue such as squinting, head position, head tilt (e.g., a user hunches over), and the relative face distance from a screen (e.g., a user is leaning in). Figure 6, below, illustrates elements of such an approach.

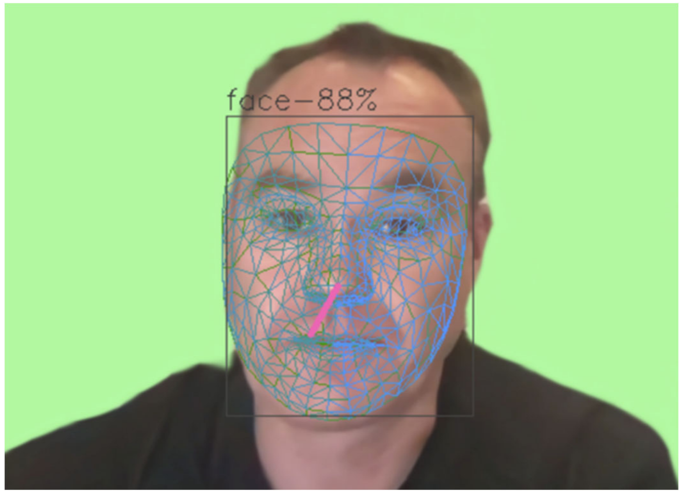

Figure 6: Illustrative Additional Indicators of Fatigue

The above-described indicators may be measured using the new ML-based video models that are available within a collaboration service. Figure 6, above, shows how head position, tilt, distance, etc. may be determined (although those items may be better seen in a video stream rather than a static image). Such indicators may be provided from in-client or on-device inferencing in real time which may be desirable from a data privacy perspective and from a performance perspective.

A central element of the second technique is the combination of the fatigue indicators that were listed above with different device-based sensor inputs. It is important to note that additional external sensor inputs may be accommodated under the second technique, but for simplicity of exposition the above narrative has focused on the closed system of collaboration service endpoint and camera input.

Figure 7, below, presents elements of a screenshot that shows a snapshot of device-based environmental sensor inputs at a point in time.

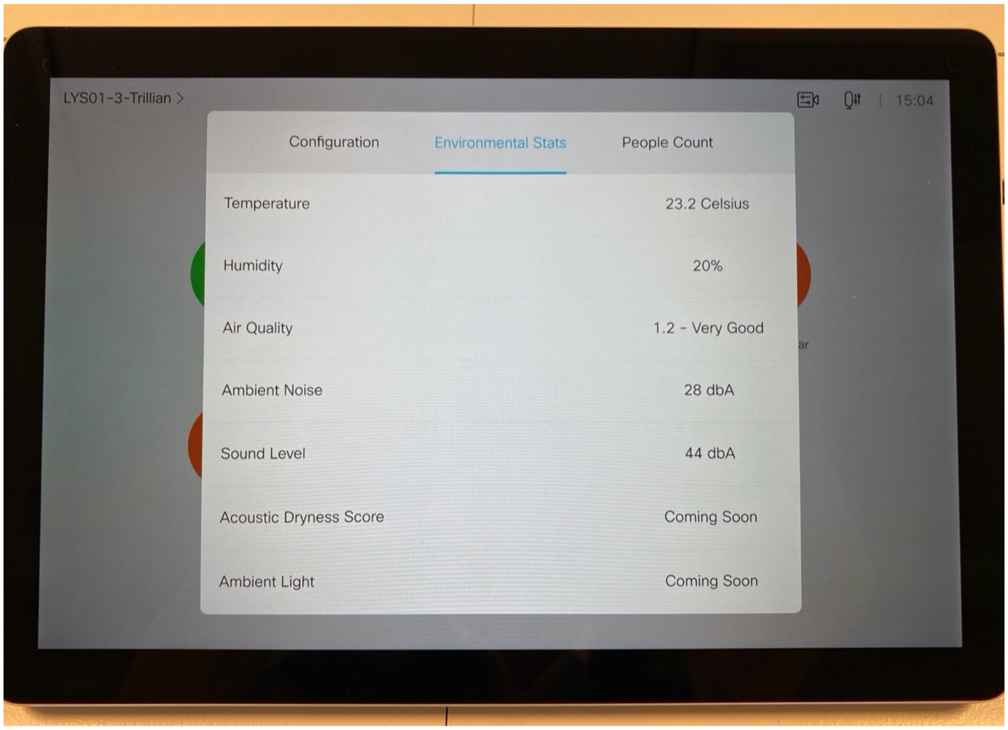

Figure 7: Illustrative Device-Based Environmental Sensor Inputs

Aspects of the second technique add a fatigue measure in combination with the environmental sensor input data that may then be stored in a user-specific profile. Combined, that data may be compared to the published standards and thresholds that were described above to provide the different insights that were identified in connection with the potential downstream use cases that were discussed above.

The screenshot that was presented in Figure 7, above, depicts generally good (i.e., productive) environmental sensor data based on the different standards. If, however, the ambient noise was greater than 35dBA, the humidity was greater than 60%, the temperature was greater than 25 degrees Celsius, and the fatigue indicator was high (as might be expected under those conditions), the system would provide insights to the user to change their environment in the interest of their wellness and productivity. Such information may be alerted as real-time insights and as a historical trend.

Historical trend data may also be used as part of the second technique to create a predictive model. When defined environmental conditions are encountered, a user may be notified that their current environment is known to cause them fatigue. Such an approach entails a personal model that may be calculated over time as opposed to comparing against industry standards as was described above.

The second technique supports a novel system and may be quite valuable to individual workers in an office, a home office, and remote environments. It may also be indirectly valuable to organizations, to know that such a system is available to individual users or by deriving organizational insights from the combined fatigue and environmental conditions.

In summary, in support of automatically detecting worker fatigue and burnout, various solutions have been provided herein through several techniques. A first technique involves a personal relative video fatigue degradation monitor, which measures the onset of fatigue over a given time period. A second technique involves a system that provides insights to reduce fatigue based on environmental sensor input for an online collaboration service.