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A PRELIMINARY APPROACH TOWARDS THE PERUSAL OF PHYSIOLOGICAL SIGNALS IN SMART-WEARABLES: REASONED APPLICATIONS AT COMSUMER-END

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ABSTRACT:

Smart-wearables, in conjunction with AI and IoT, has grown exponentially in terms of capabilities and popularity. Tasks such as measuring physiological signals, for instance, ECG and EEG are now possible on consumer-grade hardware which earlier required elaborate equipment. This fact opens new possibilities in terms of using physiological signals for various purposes. Physiological signals are activities of the Autonomous Nervous System (ANS) and provide insight towards a person's body. Using smart-wearables for constant analysis of physiological signals has several applications. As discussed in this paper, this ranges from disease detection in healthcare to emotion detection for recommender systems. Its application even extends to the security sector. With further developments in smart-wearable technology, it will be possible to get a perspicacity towards various physiological signals more accurately, which can, therefore, be taken advantage of in a broader scope. Emotion recognition is one such application which is germane in respective industries. Understanding the underlying true emotion of a user can be disruptive in recommender systems as well as human-computer interaction. This paper discusses some of the prospective applications of the analysis of physiological signals using smart-wearables. This paper also surveyed consumers, taking their views on the use of physiological signals in smart-wearables at consumer-end.

KEYWORDS: Physiological signals, Smart-wearables, Artificial Intelligence (AI), Internet of Thing (IoT)

I. INTRODUCTION

A quick reflection on any typical day reveals how Artificial Intelligence (AI) and Internet of Things (IoT) have revolutionised the world. AI, IoT and Deep Learning (DL) have opened new possibilities that were unthinkable even a few years ago. Today, AI and IoT find their applications in a plethora of fields, from suggestions on a smartphone to autonomous driving. These have intertwined themselves in our daily lives.

The increasing capabilities of modern hardware are a contribution to the advancements in AI as well as IoT. Computation has taken a massive leap in terms of performance and portability, allowing these portable devices, and their ever-connected nature in the form of IoT, to be of great use when combined with AI. Small IoT devices in the form of smart-wearables are getting fairly common these days. These are growing in terms of both popularity and capability. The recent development in this field has even allowed smartwatches to measure Electrocardiogram to a reasonably accurate level [1].

Furthermore, there have been studies delineating the use of smart caps [2] for detecting fatigue in workers using EEG. This idea can add crucial supervision over safety and security. All this opens a whole new world of possibilities.

With future advancements in smart-wearables, it will be plausible to detect physiological signals more accurately. These advancements make room for newer techniques of human-computer interaction. Studies suggest that use of physiological signals is possible for automatically perceiving a user's sentiments [3-8] having a massive impact on various applications such as recommendation systems. Moreover, studies on the use of physiological signals, for instance, EEG in detecting attentiveness and fatigue of a person exists [9-11].

Ample work has been done in the field of Medical-Science, claiming that physiological signals such as ECG can be used for detecting the emotions of a person. Physiological signals are an activity of the Autonomous Nervous System (ANS). Hence, these are an accurate reflection of the underlying true emotion of a person.

The actual state of the human body can be extrapolated from the analysis of physiological signals. Using smart-wearables for this purpose makes it possible to perform real-time analysis without user discomfort and has a large number of practical applications. This paper aims to underline a few of these applications by assessing the plausibility and considering various facets regarding the same.

II. PHYSIOLOGICAL SIGNALS AND EMOTION DETECTION

The formal definition of the word "physiology" is "connected with the scientific study of the normal functions of living things" [12]. As the name suggests, Physiological signals are measurements of various "normal" activities of the human body. Some examples of physiological signals are heart-beat rate (Electrocardiogram or ECG signal), respiratory rate (Capnogram), skin conductance (Electrodermal or EDA signal), muscle current (Electromyography or EMG signal), brain electrical activity (Electroencephalography or EEG signal).

Measuring physiological signal has historically been an involved process, demanding medical experts and elaborate specialised equipment. This complex process has been the biggest hurdle in incorporating physiological signals for any commercial purposes. However, as mentioned previously, some of these physiological signals are now being measured using consumer-grade hardware, for instance, fitness trackers and smartwatches. A number of popular smart-wearables are now capable of taking ECG. Considering this fact, it suffices to say that future advancements in the smart-wearable technology will allow the measurement of other such physiological signals with higher precision and ease.

A. ECG

Even with its constraints in the current scenario, physiological signals are seen to be a perfect feature for emotion detection in a subject. Jerritta Selvaraj [3] et al. used ECG for classifying emotions into six categories based on 2D valence and arousal model [13] using Hurst and Machine Learning algorithms such as K-Nearest Neighbours (KNN) and fuzzy KNN, getting the accuracies ranging from 92.87% to 76.45%. Luz Santamaria-Granados [4] et al. showcase the use of physiological signals for emotion detection using Deep Convolution Neural Networks (DCNN) and achieved an accuracy of 81% and 71% for arousal and valence respectively, using the DCNN on AMIGOS [14] dataset and compared performance of various classical models. Foteini Agrafioti [5] et al. replicate similar results using pattern recognition techniques. Similar studies have exhibited results with varying levels of success [6-8].

B. EMG

Emotion detection of a person using EMG signals has given great results. This fact is perspicuously stated by Khadidja Gouizi [15] et al. that EMG signals can actively detect negative emotions which is a threat to the subject's health. There is a candid connection between emotion detection, EMG for facial reaction and the executive function performed by the frontal part of the brain chaining the orchestration of thoughts and actions in accordance with internal goals. A study by Michela Balconi [16] et al. supports this hypothesis. A closer approach to facial expression evaluation via human-computer interaction conducted by Yumiao Chen [17] et al. wherein eyebrow movements were traced using surface electromyography (sEMG). The average accuracy reached was 96.12% which is quite substantial. Therefore, this evidently demonstrates that it is feasible to use EMG signals to detect the emotional state of a subject. It increases a wide range of applications for a smart-wearable system which has an EMG monitor for detecting emotions.

C. EEG

The emotions of a subject can be classified widely based on their EEG signals. There exists an engrossed relationship between the human emotions and neural activity of the brain. An elaborate comparative study on this relationship by Jingxin Liu [18] et al. provides satisfactory results using various Machine Learning (ML) techniques. The information extracted from the EEG signal is rich with essential information that subsumes the human emotions. Aayush Bhardwaj [19] et al. used the ML algorithm of Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) achieving an accuracy of 74.13% and 66.50% respectively. The future work states the possible use of emotion detection in neuro-marketing and recommender systems using EEG data.

Therefore, it is evident that emotion variations have a direct impact on physiological signals. There exists a glut of emotion recognition models based on physical aspects such as facial expression, speech and gesture [20-22]. However, these physical changes may be ersatz or suppressed by the subject and have a higher variation in terms of regionality. Physiological activity, on the other hand, cannot be controlled by the subject easily. The polygraph test, prominently known as the Lie Detector test employs the same concept. Therefore, an emotion recognition system using physiological signals can be more accurate. With further advancements in the smart-wearables sector, it can be a viable option for real-time analysis of a subject without hindering user experience.

III. APPLICATION OF PHYSIOLOGICAL SIGNALS IN SMART-WEARABLES

The previous section of the paper elucidates how one can detect emotions precisely based on physiological signals. This approach brings in a significant number of applications in various sectors. However, emotion detection and its applications are not the only utilisation of physiological signals. Physiological signals embed crucial information about a person's body. This information can be extracted and used for a plethora of applications. Fig. 1 depicts dome of the application examples.

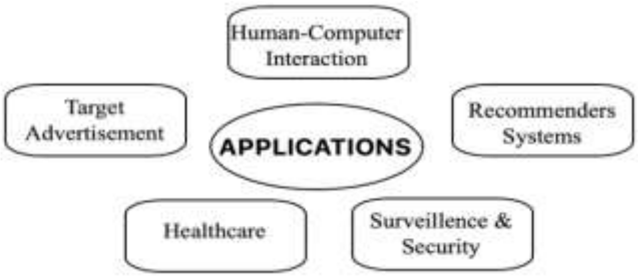

Fig.1 Applications

A. Human-Computer Interaction

Technology thrives towards speed, eliminating even the most negligible delays have been a trend since the beginning of the twenty-first century. The same trend has been followed in human-computer interactions which are continuously evolving to enhance the user experience and user satisfaction.

Human-computer interaction has matured significantly in the last few decades. However, it is not seamless enough compared to a direct connection between the nervous system and computer. The idea of communicating with a machine using our mind has been around for a long time. Analysis of physiological signals for emotion detection is a step towards this exact idea. Emotion detection using physiological signals provides the age-old idea of human-like conversations with machine a possibility, enabling naturalistic and personalised human-computer interaction. With the improvements in modern hardware, 24x7 emotion recognition can aid AI. From emotion aware AI assistants to mood-enhancing systems, the possibilities are unimaginable.

Communication in humans is a two-channel process, implicit and explicit. Natural language processing has substantially covered the explicit part. However, a significant portion of context is lost by a machine as it is unable to grasp the emotions of a person. Use of physiological signals for emotion recognition can help bridge this gap and bring conversational touch to the human-computer interaction. Roddy Cowie [23] et al. discuss this idea in detail in their paper almost two decades ago. However, the concept is still fresh and requires attention.

Emotion recognition using voice and expressions along with physiological signals, can provide a spot-on result. The next step towards a human-like AI is an emotion-aware system. Personalised virtual assistance will be able to perform emotion-specific tasks using this technology.

B. Recommendation Systems

Almost all the media that we consume today is decided by some recommendation system [24]. Most major smartphone OS now use recommendation systems to predict and recommend the apps for the users on their home-screens. The recommendation engines are a significant part of all media consumption platforms and even social media. Therefore, it is evident that any improvement in recommendation systems will have massive implications.

Recommender systems filter vital information bits out of humungous amounts of data according to a user's preferences, interests or observed behaviour. Recently, various methods for building recommendation systems have been developed. These can utilise either collaborative filtering, content-based filtering or hybrid filtering [25-27]. The recommendations in Collaborative filtering are suggested by considering the common interests and preferences of other users, whereas in Content-based filtering predictions are strongly focused on the user information only [28]. Hybrid filtering blends the best of both worlds.

Whether it be explicit feedback in the form of prompts and ratings or implicit feedback such as time spent, links opened and history, a recommendation system works extensively on feedback. It is conspicuous that recommendation engines will benefit greatly from knowing the user's true emotion or genuine opinion about the recommended item. Often the implicit feedback may be misleading and results in improper recommendations. Explicit feedbacks require user effort and hence are not ideal. Therefore, emotion detection can be of great help in identifying the actual likes and dislikes of a user, tuning the recommendations accordingly.

Recommendation for media such as music and movies can especially be impacted by knowing the emotions of a user. The system can pre-emptively determine the genre based on the person's emotions. The recommendation engine can maintain multiple profiles based on the user's emotional state, working exceptionally well for people with an eclectic taste. The subject's physiological signal extracts the likes and dislikes helping the recommendation system. Therefore, physiological signal-based system of recommendation will benefit the listener as well as the content providers.

C. Surveillance and Security

The earlier sections highlight the emotion detection capabilities of physiological signals. However, physiological signals provide much more information. EEG can be used for determining the stress and fatigue levels in subjects. This information is of great value in critical-position workers.

Using smart-wearables to supervise workers controlling heavy machinery for fatigue and stress is essential. Physiological signals can be used for checking alertness in such workers [29]. Setups such as construction sites and factories can use this technology as an added surveillance layer for ensuring the security of workers [30]. Ashrant Aryal [31] et al. elucidates the use of thermoregulation, heart rate and EEG to monitor fatigue levels in construction workers using smart sensors, achieving a combined accuracy of 82%. Attention and fatigue supervision are especially useful in hostile working environments, where worker's need to be conscientious, for instance, in the mining industry.

The attention and fatigue supervision system may also be useful for monitoring drivers. Approximately 1.3 million people die in road accidents in India every year [32]. About 20% of this is estimated to be caused by exhausted drivers. Unlike visual monitoring [33] using cameras, psychological signal-based monitoring for attention and fatigue are more accurate and overcome the privacy complaints related to camera-based systems.

The intoxicated driver is an even more significant portion of the number of accidents taking place. Hamidur Rahman [34] et al. performed a case-based study on detecting the state of intoxication marked as "drunk" or "sober" using Heart Rate Variability (HRV), Respiration Rate (RR), Finger Temperature (FT), and Skin Conductance (SC), achieving a combined accuracy of 88%. Another culprit of road-accidents is road rage. Road rage and aggressive drivers are a serious threat to public safety [35]. Emotion detection using smart-wearables can help keep a check on the same. Therefore, physiological signal analysis using smart-wearables can also aid in road safety.

D. Target Advertisement

Target advertisement has been one of the most lucrative ventures in the past decade. It has been possible due to the humungous amount of data that is available to companies. Currently, advertisements are suggested based on cookies data. This method has low accuracy and often bothers the end-user. Therefore, there is a need for a change in advertising AI system to enhance customer satisfaction and comfortability, along with improved profits for advertising companies.

Target advertising classically works purely by predicting a user's likings and showing advertisements and products accordingly. Although it is quite similar to recommendation engines, the improvements in target advertisements by incorporating emotion recognition are more direct. Extracting the genuine likes of a user and also getting the feedback of the users for every ad is a perfect example of implicit feedback. Unlike other forms of implicit feedback, such as browsing and search history, physiological signals provide a clear view of the user's views. Therefore, emotion detection can help target advertisements overcome some of its barriers.

Today, Neuromarketing industry is an added advantage to target advertising. Neuromarketing is the use of EEG or other brain activity measurement technology to measure a subject's response to some products, packaging, promotion, or other marketing components.

The subject's reaction to particular advertisements and products can be used to uplift the Neuromarketing industry. It aims to measure the response of the subject, providing perspicacity into situations where the end-consumers behaviours may be contradicting or loosely correlated to their feedback.

E. Healthcare

When it comes to health, no one is ready to compromise. Healthcare industry is the most vital sector when it comes to adopting technological advancements. In recent years, there has been a strong push towards incorporating health and fitness in consumer space. This sector is responsible for the development and widespread adoption of smart-wearables.

Today, users are becoming more conscious about their fitness and health. The consumer wants to track their health and fitness daily. Smart-wearables provide many of the fundamental fitness features, for instance, heart-rate monitoring, ECG analysis, sleep tracking and more. However, there is room for improvement.

Physiological signals have been used extensively in the healthcare industry. It has been an excellent tool for analysis of patients in a vegetative state (VS). Chris M. Fiacconi [36] et al. examined the intact emotional response of patients in VS, tracking the activity of two facial muscles (zygomaticus major, corrugator supercilii) using ECG. The tracking system can further be used in an asylum to keep monitoring the patient's emotional state, for instance, a sudden violent behaviour which is a threat to other patients, can be prevented. Furthermore, a similar approach can be used for detecting symptoms of clinical depression.

Physiological signals represent the working of the human body wherein various body systems have specific physiological signals for keeping a check on them. One of the most used physiological signals, ECG represent the cardiovascular system. Cardiologists have used ECG for detecting various cardiovascular disorders. Similar results can be achievable by the analysis of ECG for finding abnormalities that can alert patients and doctors about the presence of a disease. Smart-wearables can also help in keeping a check on patients with high blood pressure, aberration in heart-rate, and more. Fatma Patlar Akbulut [37] et al. designed the Cardiovascular Disease Monitoring (CVDiMo) to estimate long term risks of patients, achieving 96% accuracy on the same.

IV. SERVEY

The best way of knowing the consumer's point of view is via a survey. It included a questionnaire of 6 questions in which a total of hundred participants took part in the study and answered accordingly. An online form was created and circulated to 100 participants. All participants are a citizen of India. The age group of participants is from 15-75. There exists an equal ratio of men and women. The participants were not provided with any monitory fees for their participation.

S. No	Questions Asked	YES	NO	MAYBE
1	Do you own a smart wearable that keeps track of your health?	36%	64%	–
2	Are you comfortable using smart wearables for taking physiological measurements, or do you prefer conventional methods?	61%	17%	22%
3	Are you comfortable with your emotional state being monitored by your smart wearable?	54%	19%	27%
4	If you don't own a smart wearable then, would you wish to use one to improve your user experience and convenience?	69%	14%	17%

Table.1 Questionnaire for Survey

Table 1. and Table 2. contain the questions and the statistical results obtained. Apart from the questions listed in the table, the BMI of all participants was calculated using the traditional method. The BMI is used to give the fitness results based on the subject's review.

Do you own a smart wearable that keeps track of your health?	YES		NO	
	Yes	No	Yes	No
Do you believe you are a fitness enthusiast and keep a regular track of your body fitness?	82%	18%	37%	63%

Table.2 Follow up for Question1

This survey is a rudimentary step, aiming to understand the point of average users on the use of physiological signals in smart wearables.

V. RESULT

The conducted survey was successful in correspondence with the analysis provided below. A clear insight into a user's opinion helped us understand the consumer-end. Figure 1-6 presents pie-charts along with statistical data of every question in the survey in detail.

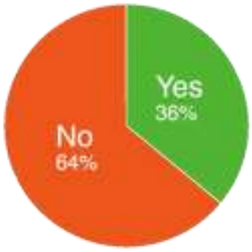

Figure 1: Do you own a smart wearable that keeps track of your health?

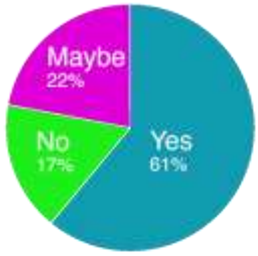

Figure 2: Are you comfortable using smart-wearable for taking physiological measurements,or do you prefer conventional methods?

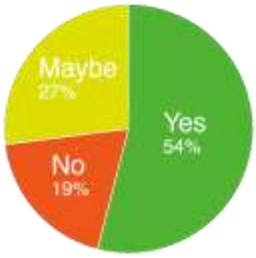

Figure 3: Are you comfortable with your emotional state being monitored by your smart wearable?

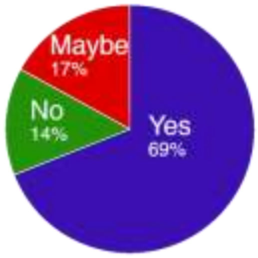

Figure 4: If you don't own a smart wearable then, would you wish to use one to improve your user experience and convenience?

For Table 2: Do you believe you are a fitness enthusiast and keep a regular track of your body fitness?

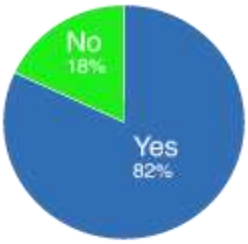

Figure 5: People with Smart-wearables

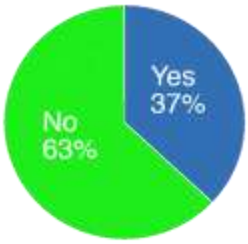

Figure 6: People without Smart-wearable

The above results show a clear trend in terms of people's awareness of health and fitness. Users of smart-wearables are more inclined towards health and fitness. The reason behind this is that the current scenario of smart-wearables is primarily focussed towards health and fitness. Another key observation is that a significant portion of the participants feel comfortable with the use of smart-wearables for emotion recognition at the cost of convenience and better user experience. Therefore, smart-wearables technology can further be expanded in this field to provide better consumer-end utilisation.

Further, a critical analysis was inferred with the acquired data of BMI of hundred subjects. According to the survey, the subjects were divided into four categories.

a) The subjects who have smart-wearable (SW) and are fitness enthusiasts (FE).

b) The subjects who have SW but are not FE.

c) The subjects who do not have SW but are FE.

d) The subjects who do not have SW and are also not FE.

The relationship between these four categories and their respective BMI helped in understanding the overall fitness of the subject. Fig 7. presents the graphical representation of the result analysis.

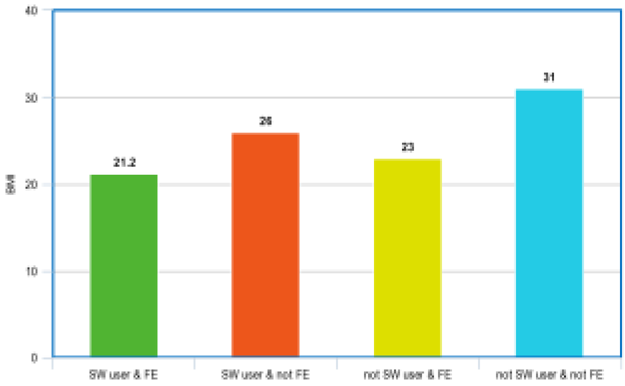

Figure 7: BMI of various groups

The normal range for BMI is 18.5-24.9. It is evident that the subjects who use smart-wearable and also keep track of their fitness are healthier compared to others. Moreover, the participants who do not use smart-wearables and also do not keep track of their health resulted in having higher BMI than others. Therefore, it can be derived that subjects who own a smart-wearable are more likely to use the fitness tracker to take care of their health.

This result suggests that smart-wearables can expand its application to the ones outlined in this paper. According to the survey, participants are willing to use smart-wearables which uses physiological signals to detect emotion and provide them with extra features. This change in smart-wearables will increase consumer-end satisfaction, comfort as well as user-experience. The study also indicates that smart-wearables can be expected to grow in terms of popularity and adaptability.

VI. CONCLUSION

Currently, the unique selling point of smart-wearables is health and fitness. However, with the incorporation of the applications discussed in this paper, smart-wearables are likely to gain even more popularity. History is proof that humankind has always chosen convenience above all. Smart-wearables have the possibility to provide unmatched convenience. They provide comfort along with function.

As the paper elucidates, the use of physiological signals in smart-wearables makes them much more functional, adding to their versatility. Use of smart-wearables in healthcare is just the tip of the ice-burg when it comes to their possible functions. The widespread adoption of smart-wearables and physiological signals is inevitable; all it needs is a push in the right direction.

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