Emotion Recognition: Benefits and Challenges

Arindra Kumar Das
MSc. ICT Innovation
University College London,
London
arindra.das.14@ucl.ac.uk

ABSTRACT
The project aims to increase the motivation for healthy adults doing squats by recognizing the affective state and providing feedback and personalized exercise plan.

Author Keywords
Exercise; motivation; body expression, Kinect, Wearables

CONTEXT
This project is done as a coursework for the Affective Computing and Human-Robot Interaction. The project initially involved three MSc. ICT students. However, a student dropped out of the course in the middle. The project involved recording of various physiological and biomechanical data while an individual was doing half squat. This data were collected from the three students involved in the project before one of us dropped out, therefore, the project was still continued using the data of all the three.

LITERATURE REVIEW
Physical activity and exercise are presumably the most important factor to drive mankind [8]. Previous studies have clearly documented the health benefits of physical activities in one's life. An active lifestyle has a huge positive impact on both physical and mental health. Regular physical activity can improve the health outcomes preventing them from diseases and developing long-term health problems and reduce expenses on doctor's visits, drugs and hospital admissions [1].

According to the government norms on physical activities, in average an adult should do at least 150 minutes of physical activities apart from adding at least two days of activity to improve muscle strength which would include strength training and exercise with weights [2].

The recent trends show that the recommended levels of physical activity are low among UK population. Specifically, as for 2008 only 45% of men in Scotland meet the recommended targets as compared to 39% in England, 37% in Wales and 33 % in Northern Ireland while 56% of women did not participate in any sports and exercises [3].

According to a nationwide (UK) survey, carried out by Health and Social Care Information Centre (HSCIC) in 2007, crucial barriers (both practical and psychological) were recognized that prevented people from involving in any kind of physical activities or exercises. The major barriers included the lack of time due to work commitments despite that woman also chose caring for children or elderly people over physical activity. Lack of money among the young age group and physical limitations and long-term conditions by elderly people were some other predominate factors. Lack of motivation was also identified as one of the major barriers by 21% of men and 25% of women [3].

Motivation plays an important factor in exercise and is a part of the behavioral theory [18]. It can be either extrinsic or intrinsic. Extrinsic motivation is triggered by one's expectation of obtaining a positive outcome for doing an activity, which can be different from the activity itself whereas intrinsic is one's willingness to do a task without being driven by an external factor [17].

There is a negative influence in self-efficacy and affective states when doing exercises, whilst effecting the motivation to continue the physical activity [6]. People tend to avoid unpleasant experiences and intensity of exercise and the affective responses are correlated. A greater intensity during exercises affects the affective responses resulting in a decrease of motivation and chances to reduce cohesion while having a high chance of dropping out [4]. As this is described in the Hedonic theory for motivation as the behavior based on a person's willingness to maintain and continuation of an activity based on the level of satisfaction [7].

Motivation can be measured based on one's engagement in an activity to obtain a result [16], while engagement is the notion of one's involvement into an activity both bodily and cognitively [15]. This affective response influences the decisions of whether to repeat the behavior or not [20].

Affect is the basic characteristic to all valence responses that also includes emotions, feeling and moods as well. Affect may or may not occur with each emotion. Don Norman describes

"Emotion is the conscious experience of affect, complete with attribution of its cause and identification of its object [42]."

Few examples of affect would include boredom, engaged, tired, irritated, excited, depressed etc. [4]. Individuals' affective responses are active to factors such as personal, social, physical and physiological factors while doing physical activity [5].

This project chooses engagement and disengagement as the affective states towards trying to find out solutions to increase the motivational factor.

Technology

Due to all the barriers a long-term commitment to exercise is difficult. Insufficient knowledge about exercise makes it further more difficult to maintain long-term exercising. Personal trainers have significantly increased the motivational level while providing personalized advice and continuous monitoring of the success [21]. The cost of the personal tutor is increasing which makes it difficult for individuals to pursue it as an option [22].

On the other hand, the wearable and sensing technology are being developed in a fast pace. Personalized monitoring in case of pedometry has proven to increase the motivational level of individuals [23, 24, 25]. This opportunity is very well exploited in the market with commercial devices such as Fitbit, Jawbone, Nike fuel band and mobile applications such as Runkeeper, Move etc. The primary target for these companies is in running and walking. Further, consoles such as Microsoft Kinect, Nintendo Wii usually target the outdoor sports in an indoor scenario [26].

There is not much research on tracking device for weight training and calisthenics. recoFit a wearable sensing device provides a way to track this. It has three models, segmentation, recognition and counting, Segmentation: detects the change of two different exercises, Recognition: automatically labelling various exercise and Counting keep tracks of number of repetition [26]. However, they do not include the detection of affective state in weight training and calisthenics that can further provide feedback on how to improve while staying motivated.

Squat

As mentioned in the earlier section, a healthy adult is recommended to do two-day weight exercises. The squat is the most common strength exercise and is also used for conditioning. It is also referred to as the "king of exercise" [9]. It is a core exercise being performed by athletes and personal trainers as part of their normal routine. Squat has biomechanical and neuromuscular similarities to a broad range of athletic and power lifting movements; and involves various muscle groups in a single maneuver improving the quality of life [12] primarily hip, thigh, and back musculature [13]. It is also often associated with natural postures in once daily activities such as defecation postures [10], lifting packages etc.

Even in a clinical setting it is used for knee rehabilitation in cases such as anterior cruciate ligament (ACL) injury, patellofemoral dysfunctions etc. by strengthening lower-body muscles [11].

As described by Starting Strength Website as

"There is simply no other exercise, and certainly no machine, that produces the level of central nervous system activity, improved balance and coordination, skeletal loading and bone density enhancement, muscular stimulation and growth, connective tissue stress and strength, psychological demand and toughness, and overall systemic conditioning than the correctly performed full squat. [14]"

There are different kinds of squats that can be carried out. All kind of squat adds to the strength of legs, hips and core muscles, which provides a strong foundation [41]. However, there are biomechanical differences between different squat and individual should select the squat based on the kinematics that suit the training goals [40].

The squat can be performed with various degrees of knee flexion, for example, the half squat or full squat. In this project, we use half squat. In a half squat, the person comes to a squatting position until the thighs are parallel to the ground with approximately 0–100° knee flexion. [19]

Objective

In this paper, we investigate the use of technology to increase the engagement factor using a single exercise which squat. A recognition model would detect the engagement factor of the squat, which will be later used to develop feedback systems that could increase the motivation.

Body and Face expression

Affective computing is primarily focused on facial expressions [28], [29]. Body postures have not extensively been used to recognize affective states. As facial expression was considered the main indication of emotion recognition for a long period of time [33] also body was meant to be more complex [30]. However, studies have provided evidence about body expression as an important source of non-verbal communication [31][32].

Kleinsmith A. et al have pointed out three possible arguments supporting body expression: Firstly, there are research evidences showing that body expression have similar relevance as facial expression in detecting emotion. Secondly, the daily activities of a person include multimodal interactions, which go beyond facial and gestures. Thirdly, our body is seen as an important non-verbal communicator culturally, clinically and socially, for example a teacher can read the various affective states of a student to understand the problem the student are facing etc. [34].

In a clinical setup, like chronic rehabilitation there are movements and body postures that communicate emotional turmoil that a patient experiences which are then used by clinician to create tailored treatments [43][34].

As squat involves various muscle groups that are associated with bodily postures and movement, and moreover physical exercises exert intense emotional and affective reactions, which are better communicated through body expressions then facial expression [44]. Therefore, to build this recognition model we use body movements.

Acted and non-acted sets.

In an attempt to label various body expressions for the recognition model it was found that both acted and non-acted sets have their pros and cons. Acted expression has an extensive research compared to non-acted however acted expressions can be highly biased. On the other hand, bodily expression varies from individual to individual in a multitude of reasons such as age, culture, context, gender, posture, culture, past experiences etc. [46] making it more difficult to build an ideal recognition model with using acted set, while in contrast non-acted sets are complex [34] [27].

Previously studies to detect bodily expression were conducted individually on either acted [45] [47] or non-acted sets [27]. In acted sets the body expressions were labeled by providing specific guidelines on various specific states and the participants were referred to as actors [47], whereas, external observers labeled non-acted sets [27].

In our study, we consider both acted and non-acted sets of body expression and analyze them to find out discriminative features and also find out contrast between both methodologies. So moving from an easy situation to moving to a complex situation.

DATA COLLECTION

Sensors

Data was collected from three different hardware: Empatica, Kinect Xbox One and Apple Mac Laptop. Empatica is a wristband that was used to monitor Galvanic Skin Response (GSR), accelerometer data and Blood Volume Pulse (BVP). Kinect sensor was used to capture body motion data in form of blob and depth video. They were used to collect features for the recognition model. The different hardware was used to capture different form of modalities possible including physiological data. However, from initial assessment, the Empatica data does not look to provide much information, as it is difficult to differentiate between exercise- and emotionally- induced activity.

Apple Mac Laptop's in-built camera acted as a normal video camera used to capture the video. Video was recorded for observers' labeling and also to determine ground truth

Participants

Three participants were involved in the project (For participant info see the *Context* section). All the participants were healthy males aged 25-28 years old with previous knowledge of squat. They were involved in regular exercises and had no pain or Long time condition during the course of study.

Setup

The data was collected inside a closed space with only the three students involved in the project, so the environment was friendly and comfortable. All the participants were wearing casuals. The Kinect sensor and Mac were put in front of the participant to record while the Empatica was worn in the right wrist by the participant. There was no marked foot position in the ground however, all the participants were asked to follow a horizontal reference line so that the Kinect can detect and capture the whole body of the participant. Later, it was found out that for not having a marked foot position, the horizontal distance between participants varied making it difficult for normalization.

Process

The participants were asked to do acted and non-acted sets of squats. During the acted set four affective states were performed i.e. engaged/disengaged and energetic/tired with 5 squats per set. This was followed by two non-acted sets of 20 squats with 2 minutes interval. The whole process was repeated twice by all the three participants, producing 120 acted and 240 non-acted squats. All the data were chopped into individual squats for next steps.

LABELLING

As mentioned above, the labelling for the acted sets were done based on the participants' idea about each affective state: engaged/disengaged and energetic/tired.

There was a large amount of non-acted squats (240 squats). As in a short period it was not possible to label all the squats, only 60 randomly selected squats were taken. 12 sets each including five of these squats was formed. It was made sure that each set would include atleast a single squat of all the participants. The squats were in form of video-snippets. These 12 non-acted sets were labeled using external observers producing 60 labelled squats. For labeling this 12 sets comprising of five non-acted squat video-snippets each, 12 external observers were recruited. All the observers were screened to make sure they themselves have done squats before and have knowledge about it. Consent forms were signed showing their interest to participate in the research without any benefit. All the observers were UCL students with a mixture of males and females in the range of 21-28 years in public spaces. Each of them was asked to label two different sets, one for engaged/disengaged and the other for energetic/tired. Each video snippet was of 30-50 seconds and the total time taken by each observer to label was 2-4 minutes. The participants were explained that based on their knowledge of engaged/disengaged and energetic/tired they should label the data and the choice was fully subjective. However the energetic/tired was not included in the datasets as lack of motivation was primarily focus on the engagement factor and to keep the complexity low. The faces of the participants were not covered; therefore there might be consequences of facial expression biasing which needs to be considered.

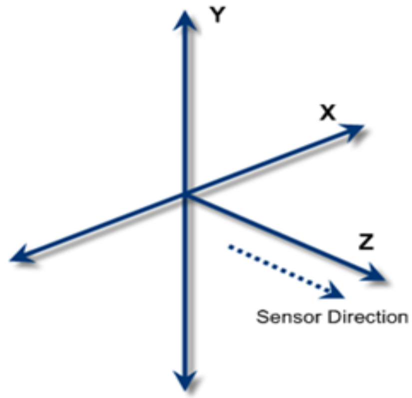

Figure 1. Kinect coordinate system

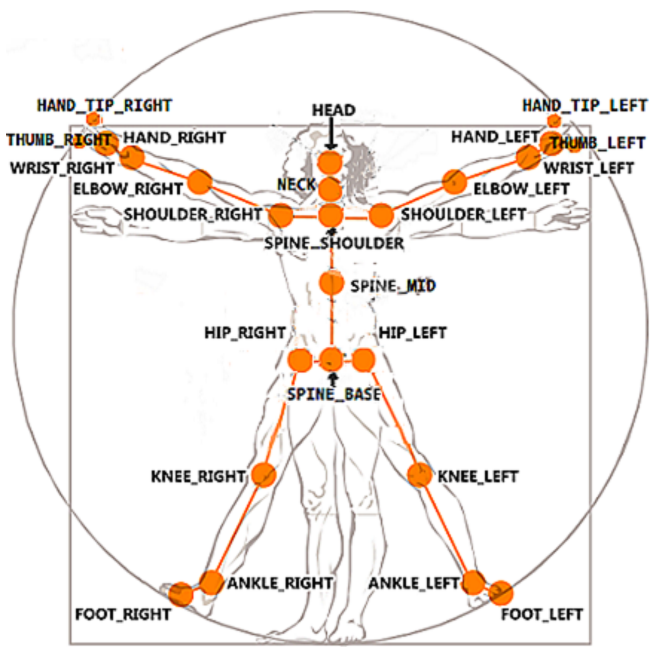

Figure 2. Skeleton points returned by Kinect's API (circles) and defined body parts.

FEATURE EXTRACTION

We select the features only from the Kinect sensor. There are 3 axes to that Kinect (X,Y and Z as shown in Figure 1) and 25 markers in each axis (see Figure 2 and Table 1) [51]. These produce 75 total features.

Segments	Attributes
Cervical and thoracic spine	Head, neck, spine, spine base, spine shoulder
Left arm	Left shoulder, left elbow, left hand, left wrist, left fingertip, left thumb
Left leg	Right shoulder, Right elbow, Right hand, Right wrist, Right fingertip, Right thumb
Right arm	Right shoulder, Right elbow, Right wrist, Right hand, Right fingertip, Right thumb
Right leg	Left shoulder, Left elbow, Left wrist, Left hand, Left fingertip, Left thumb

Table 1. Markers of Kinect

As squat is done vertically, which is corresponding to the Y-axis and after verifying with statistical analysis that shows irregularities, the X and Z-axes are discarded (see Figure 3). After removing these axes we are left with 25 features.

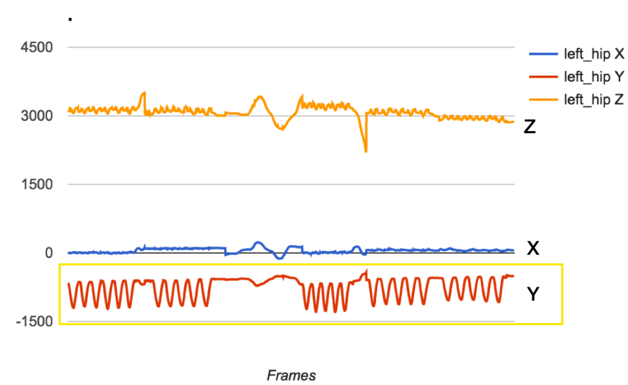

Figure 3. Graph showing the irregularities of X and Z axes, while Y-axis (highlighted in yellow box) shows perfect squat cycles.

The foot and the ankle position of both right and left legs are removed, as they are constant without any movement during the exercise. Then the features are reduced to 21.

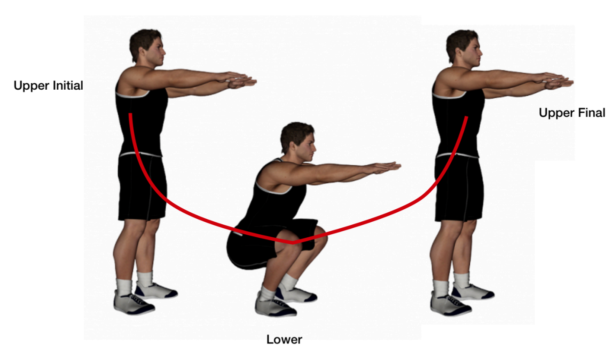

Figure 4. Complete squat cycle (Upper initial-lower-upper final position)

A squat cycle is completed when the individual starts from an initial upper position then go down until a lower position and again come back to the upper position (see Figure 4) [19]. We take the initial upper position of each squat, the lowest squatting position and the final upper position of each squat into consideration. High-level body descriptions are also a good way to determine affective state [34]. Therefore for each 21 feature there are 3 positions, which make the total feature to 63.

Finally, we have 64 attributes with 63 feature attributes and a single class attribute that describes whether a squat is engaged or disengaged.

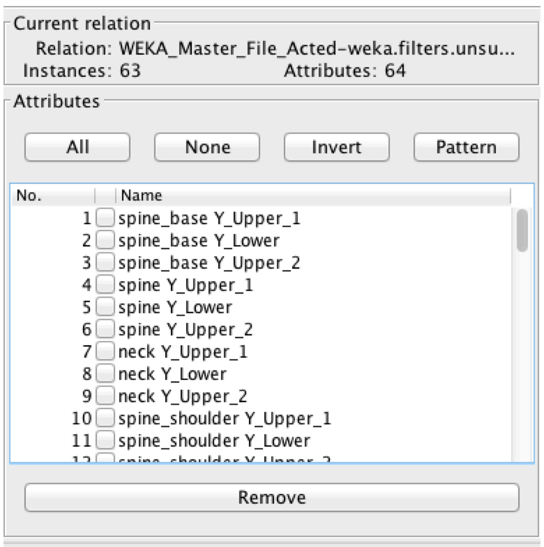

Figure 5. Screenshot of Weka software loaded with acted set

FEATURE MODELLING

Seven classification algorithms, Naïve Bayes, SMO, J48, k-NN, OneR, ZeroR and Random Forest (RF), have been used for automatic recognition of affective states. We used Weka Version 3.6.12 [49] for the implementation. Both acted and non-acted set were run through all the above algorithms (except ZeroR) using 10-fold cross-validation method. Whereas ZeroR was used to find the baseline accuracy using only the training set.

Method	Accuracy
Zero R	51%
OneR	57%
Naïve Bayes	68%
Nearest neighbour (IBK)	75%
Random Forest	73%
J48	81%
SMO	78%

Table 2. Acted sets

a	b	<-- classified as
27	4	a = Yes
8	24	b = No

Table 3. Confusion matrix for a 10-fold cross validation training of the J48 algorithm.

In acted set, J48 achieved the highest performance with 81% accuracy. J48 produces decision tree with 5 leaves and 9 trees. “right_fingertip_lower”, “right_wrist_lower” and “right_elbow_lower” are the purest node with “right_fingertip_lower” attribute being having the highest information gain.

After running J48 several times removing the pure nodes, it was found that the accuracy was always decreasing. It made us come to a conclusion that datapoints in the arm plays a very important role in squat.

Method	Accuracy
Zero R	65%
OneR	47%
Naïve Bayes	43%
Nearest neighbour (IBK)	52%
Random Forest	55%
J48	60%
SMO	60%

Table 4. Non-acted sets

In Non-acted set, we find out that the baseline accuracy value outperforms the other methods i.e. ZeroR (with training set) have the highest performance of 65%.

According to theory [50], if the baseline accuracy is more than the other machine leaning algorithms the dataset is not good. This might be the case because in case of non-acted sets the observers who might have varied opinion labeled the data.

Method	**Accuracy**
Zero R	50%
OneR	38%
Naïve Bayes	43%
Nearest neighbour (IBK)	52%
Random Forest	52%
J48	52%
SMO	67%

Table 5. Case1: P1+P2 used as train set whereas P3 used as test set.

Method	**Accuracy**
Zero R	50%
OneR	65%
Naïve Bayes	45%
Nearest neighbour (IBK)	55%
Random Forest	50%
J48	45%
SMO	55%

Table 6. Case2: P2+P3 used as train set whereas P1 used as test set.

Method	**Accuracy**
Zero R	50%
OneR	55%
Naïve Bayes	55%
Nearest neighbour (IBK)	50%
Random Forest	73%
J48	82%
SMO	59%

Table 7. Case3: P3+P1 used as train set whereas P2 used as test set.

Cases	**Accuracy**
1	67%
2	65%
3	82%

Table 6. The highest accuracy from cases 1-3 in a leave one subject out validation

Finally we carried out leave one person out where we divided the acted dataset according to three participants (P1,P2 and P3). The best performance provided by each cases (see Figure 3-6) is used to find the mean. The performance is 72% for this case.

EXERCISE PLAN

Physical activity should be considered as an evolutionary and adaptive process [4]. Systematic training program would improve the adaptation of the body to the exercise performed. Therefore, it is important that an exercise plan should be designed accordingly, Zatsiorsky [48] mentions four features of adaptation process that can be important while planning and executing training program: *stimulus magnitude (overload)*, *accommodation*, *specificity* and *individualization*. In summary, the training load should be relatively higher than the habitual load, the training process becomes inefficient if the same training load is done over a long period of time and same kind of training methods for everyone may be ineffective while encouraging individual plans.

According to Government norms and personal training evidences, weight training should be done twice a week. Due to involvement of various muscle groups each weight training has special needs. Here we provide a plan for half squat. Depending upon the expertise level the basic structure of squat training includes a series of sets with each set comprising of repetitions. It is important to note that exercise done incorrectly can have negative affect, especially weight training, such as squat. This could have severe back and spinal injuries [41]. Therefore, it is very crucial to have a exercise plan as well as a feedback system that could monitor during exercise.

Various training programs start with an initial test that could determine the current fitness level. This initial test would ask the individual to do as many squats they can do, with caution so that they do not push themselves to an extend of injury/pain. Squats are not recommended during any injury. Based on the initial test, there are specific training programs with goals [54].

Although there are various exercise plans and training program there's' lack of motivation, fear of doing the squat wrong etc. However, game is found to be an important source of motivation in exercise. During recent years games are built to motivate people to get out of their sedentary state. This is been successful due to being fun and feeling of accomplishments [53].

Game increases the engagement, self-efficacy and high adherence to continue. This have been extensively used by many console game developer such as Nintendo Wii; manufacturer of fitness equipment such as Technogym, who have implemented virtual running scenario into their treadmill interface [35]; mobile applications such as TripleBeat that facilitate runners through virtual competition and so on. But, most of the gamification techniques are used in aerobic activities [39].

According to Fogg, a persuasive technology tool is "an interactive product designed to change attitudes or behaviors or both by making a desired outcome easier to achieve" [37]. Fogg have identified seven common strategies of persuasive technology: i.e. reduction, tunneling, customization/tailoring, suggestion, self-monitoring, surveillance, and conditioning [36]. Implementing gamification into exercise has shown great results and can be used as a major persuasion tool. Gamification overlaps with four strategies out of seven strategies of persuasive tools: tunneling, self-monitoring, surveillance and conditioning [38]. Tunneling is the step-by-step process of completing a task to reach the next milestone, self-monitoring and surveillance are to do with tracking the performance data and conditioning would mean positive rewards and feedbacks.

Taking all this information into consideration a feedback system can be implemented that could also act as a personal coach.

FEEDBACK SYSTEMS

Squat can be performed in different places such as in a home setup or gym, the context is important to design a feedback system that do not interrupt or provide distraction to the others around. While headphones, smartphones and laptops are commonly used during exercises depending upon the context, in a gym setting this might cause potential problems such as absence of environmental awareness effecting distraction to others, obstacle in hearing emergency alerts, unexpected accident such as dropping weights etc. On the other hand smartphones are quite bulky to carry around during workout. Therefore, there is a need of a more ubiquitous sensor that does not interfere in the activities while providing a smooth experience and maintaining the engagement level of the individual until the exercise plan is completed.

Feedback can be provided through sound, music, vibration, display, light etc. Music, sound and display were not considered due to the context of gym and moreover it is not safe to wear headphones. Therefore, vibration and lights were used for feedback to reduce less distraction and greater experience as squat is a critical activity and requires much more concentration.

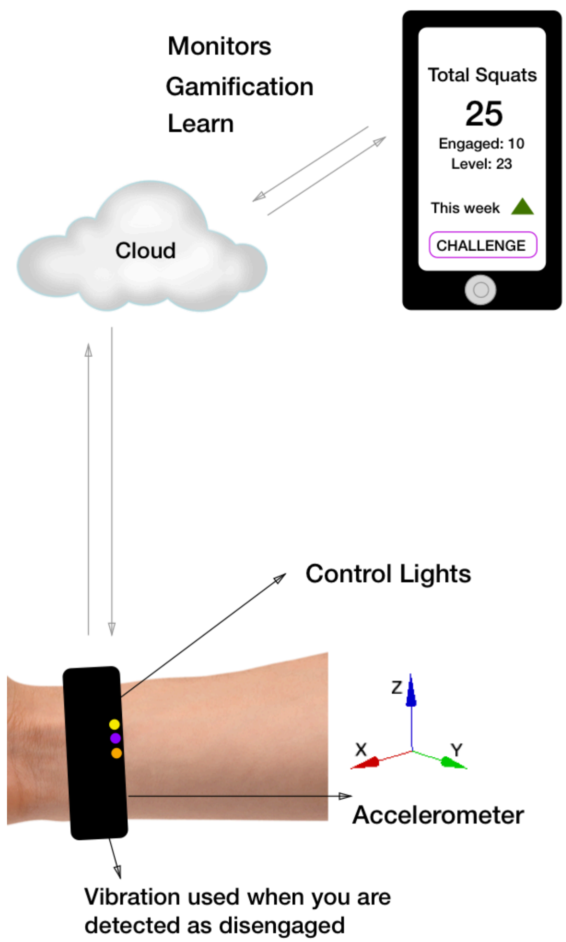

Figure 6. Feedback system

We propose a wearable device that can be worn easily in the arm, as the most discriminative features were in the arm. The device would include an accelerometer that will be aligned according to the Kinect's coordinates (X-Y-Z axes), a vibration sensor to provide feedbacks on disengagement which would also mean it would effect their level and lights for control signals. The wearable can be connected with cloud to sync the data with a mobile application that would maintain the profile of the user. This mobile app would provide personalized exercise plan with daily, weekly and monthly milestones (tunneling); a daily log (surveillance); maintain gamification profile such as scores, challenge etc.; remind the user to do squat and also provide improvements and positive feedbacks (conditioning).

The app starts with creating a profile and checking for health issues that might affect you during squats. Then the device can be used. The device starts with initial calibration asking the individual to squat; control lights would show indication of the devices' states. Once the calibration is competed, the device would ask for an initial test to see the level of the user (novice, medium, expert, etc.). The next step would be a personalized exercise plan to follow with different milestones.

DISCUSSION

During the feature modeling, it was found out that almost all the discriminative features were in the arm for acted set. However, this was quite different from what we assumed, which had its main focus on knee and hip.

We were interested to detect the affective states by body movements and postures while doing squat. But while being labeled by the observer the facial expression was predominant, which might have been affecting the result of non-acted set. In contrary with more information, we would have a better ground truth, which meant face expression would have been an advantage. However, since we were detecting emotional states the ground truth was anyhow difficult for us to determine [54].

As for the non-acted set, the baseline accuracy was higher than the rest of the machine-learning algorithm; therefore, our dataset was not labeled correctly [50]. However, we should divide the dataset into two random subsets, and try to evaluate one of the subsets by experts (personal trainer) and the one by the researchers itself. Later using interobserver reliability between the two subsets try to see if there is a good agreement between the researcher and more by the expert to trust the dataset [27].

However, in future to check that if 81% performance in the recognition model can be trusted to be market ready, the current model could be compared and verified with the system with the views of experts and professionals in the field of physical activity.

CONCLUSION

This project started with the importance and need of physical activity and weight training for an adult to stay healthy. Lack of motivation was found as one of the barriers. Motivation means engagement towards continuing the exercise, therefore engage was chosen as an affective state. There is less evidence about technologies and research studies that can help motivate people who does weight and strength training. Therefore, a novel approach to build a system that could identify and provide feedback on weight training to increase the motivational level has been discussed in this paper. Body expression was used along with both acted and non-acted sets of squats. 81% accuracy in acted set was found out along with all the discriminative features being from arm. A feedback system was proposed that included gamification and wearable device to help increase the motivational level.

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