# Proper Running Posture Guide: A Wearable Biomechanics Capture System


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## ABSTRACT

Running is a popular exercise for all age groups. It helps heart and lung functions, enhances muscle strength and control weight. Nevertheless, excessive fatigue and severe injury resulting from inappropriate running poses might reduce the benefits brought by this exercise and stop people from keeping running regularly. In this paper, we design a system that can monitor the running biomechanics, infer running poses, analyze running patterns, and provide both real-time and off-line feedbacks to reduce unnecessary fatigue and unwanted injuries. Common inappropriate running patterns, over-striding, over-pronating and out-sync, are identified and analyzed with the continuous wearable sensor data streams. Two types of correctional feedbacks are designed to provide users appropriate adjustment guidance: vibrating the areas of user body where improper poses are detected and visualizing running video with sensor waveforms to indicate which inappropriate motions trigger the vibration. With reasonable adjustment, running can be a safe and effective activity for a healthy lifestyle.



## Categories and Subject Descriptors

H.5.m. [**Information Interfaces and Presentation (e.g. HCI)**]: Miscellaneous

## General Terms

Design; Measurement; Running; Wearable Computing; Motion Detection and Activity Recognition.


## 1. INTRODUCTION

Running is a great means to keep the body healthy; moreover, it may enhance brain health and plasticity [6]. A research [8] among aging runners also indicates that running can benefit health and cognitive function, and running can slow down ability declination. What is more, a public health research [13] indicates other exercises cannot replace running when dealing with adiposity. Running properly may seem like an inborn ability, but realistically it is a skill that needs to be learned and practiced. Running in improper poses may lead to injuries and other issues. Over-striding and over-pronation can be two serious mistakes in running, as they will bring injuries such as shin splints [1]. In addition, people increase fatigue rate as performing those improper movements wastes energy. To diminish these issues, in this paper we present the technology of using sensors to help people correct their running posture.

A number of researches [16, 5, 14, 12, 15] and products [2, 3, 4] make use of body sensor networks to track and analyze users' motion during exercise. However, they are generalized to monitor several exercises rather than to focus on running motion correction. These existed attempts do not provide feedback and cannot efficiently prevent injuries due to bad running habits.

The first step is to detect specific motions during a runner's stride that can often lead to inefficiency and injury. An efficient runner's stride consists of a sequence of motions that correlate properly to create safe and efficient movements. When incorrect motion occurs, a chain effect is developed in which the body reacts to compensate for these motions. Consequently, the compensatory motions lead to further inefficiency and increase the risk of injury. After detecting running mistakes, our system will send correctional feedback to the user. The vibration feedback, on user's body where exhibits improper motion, can lead to a safe and efficient stride at the subconscious level. Graphical feedback, showing running video with waveforms from sensor data, helps users understand their improper running style.

## 2. RELATED WORK

Commercial products in exercise monitoring become popular these days, Fitbit Flex [2], Jawbone Up [3] and Nike+ Fuelband [4] are three best selling wristband among US. They have similar functions: set exercise goal for the user, monitor users' activities and reward users by sharing exercise record with the user community. These products aim at determining whether the user is doing exercise and estimate calories consumed. They do not classify which exercise user is doing and cannot correct user's exercise pattern.

Researchers also use body sensor network to track and analyze users' motion during exercise. One research [12] attempts to use wearable sensors to analyze runner performance comparing with professional athletes. However, it only discriminates different performance groups based on vertical oscillation and foot contact, without detecting improper running patterns to notify runners. MyHealthAssistant [10], a phone-based body sensor network, uses 3D inertial sensors to capture user's exercises. It recognizes exercise patterns, counts exercise times and provides a fitness diary with heart rate and other health information. Another research [9] also tries to recognize user activity from accelerometer data, using base-level classifiers and meta-level classifiers. Although last two researches can be accurate in determining which exercise is performed, they are not designed to determine the quality and correctness of exercise. Exercise counts and quality are both important, because if the user does exercise in the wrong manner, it may hurt rather than help. Therefore, running posture correction is necessarily needed.

# 3. SYSTEM OVERVIEW

We first develop algorithms to detect over-striding, over-pronation, and improper correlation between the runner's limbs. These motion patterns are common among runners who run improperly. After recognition, our system sends correctional feedback to the user. As the runner instructs muscles to move at a relative high speed during the stride, it is very difficult for the user to detect his/her own motions at the conscious level. Our system triggers vibrational feedback on the part of body where exhibits improper running motion. This feedback warns user in a short time and improves running motion at the subconscious level to produce a safer and more efficient stride. Our system also provides running video feedback with synchronized waveforms from sensors on body. This feedback will allow users to see which improper motion triggers the vibration feedback.

Our system uses Microleap2 platforms which have accelerometers and gyroscopes. Due to sensor noise, accelerometers and gyroscopes are more suitable in detecting motion than precise angles, distances, or positions. Thus, we focus on the relevant body parts motions instead of exact position of movement.

# 4. SYSTEM DESIGN

## 4.1 Data Collection

As seen in Figure 1, running data is collected by five microleap2 devices located on the runner's elbows, knees, and waist. The microleap2 devices transmit data over Bluetooth to a paired laptop. We collect data with the subject running on a treadmill through btrelay and btclient software in Professor Kaiser's lab. These software produce a file stream associated with each device and work well with multiple sensors. The data from each of the sensor are synchronized at 60Hz sampling rate for each microleap2 device. This sampling rate provides us with high enough resolution to capture a runner's movement without bandwidth issue. Our system also records running video so that the runner can see his/her motions with sensor data.

## 4.2 Signal Processing

The first step of signal processing is to generate frames. The frame size in our system is 180 samples in each 3 seconds. This frame size

**Figure 1: The placement of the Microleap2 devices.**

ensures to get enough data for three to five strides and also keeps the temporal resolution high enough to trigger feedback for current movement without noticeable delay. After acquiring the frames, our system starts to detect over-striding and over-pronation.

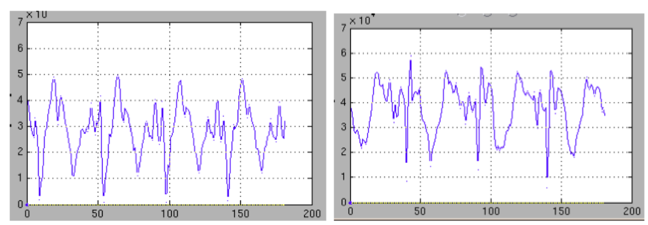

**Figure 2: Left: Not over-striding X-axis acceleration. Right: Over-striding X-axis acceleration.**

Over-striding occurs when runner's foot strikes the ground in front of body center of gravity. In this case, the braking force slows down the runner and exerts force on legs, hips and back. Consequently, over-striding is a dangerous movement which needs realtime detection. The algorithm should quickly process the impact force while requires little training. To determine over-striding, we decide to extract specific features from the waveforms. The features we choose are the peak magnitude and the peak width along the X-axis (parallel with runner running direction) of the runner's legs. We find distinct peaks when the runner's foot strikes the ground. The peaks are associated with the change of the runner's foot direction; therefore braking motions create a evident acceleration change, which is shown as steep peaks. As seen in Figure 2, the peaks of the over-striding waveforms are sharper and occur in shorter time. After taking the peak magnitude and dividing the magnitude by the peak width, we obtain a metric to determine whether a runner is over-striding. We then set the threshold based on the metric values from five different runners performing over-striding and not over-striding. We used this metric threshold to detect over-striding.

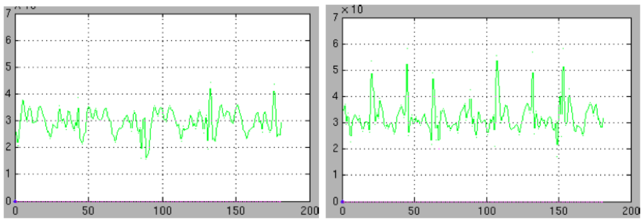

**Figure 3: Left: Not over-pronating Z-Axis waveform. Right: Over-pronating Z-Axis waveform.**

Over-pronation occurs when the ankle rolls inward during impact. The nature of runner's foot often causes it, and people usually correct it through orthopedic shoes or inserts. When a runner is over-pronating, he/she will often experience pain in the foot, ankle, knees and back. Therefore, it is also very important to fix this behavior, same as the motivation of over-striding correction. One characteristic related to over-pronation is that the runner exhibits lots of lateral movement in the legs from side to side. This lateral movement can be detected in the Z-Axis of the accelerometers located on the runner's legs. As seen in Figure 3, the runner without over-pronating produces little deviation in the waveform. On the contrary, the over-pronating runner produces more obvious deviation in the waveform. By taking the standard deviation of the frame, we are able to get a metric to indicate the extent of over-pronating. Although the algorithm is relatively simple, it detects over-pronation consistently without calibration or gravity compensation. Due to these factors, we use this simplistic yet effective algorithm to detect over-pronating.

## 4.3 Correlation and Mutual Information

In our system, we detect improper running behavior such as over-striding and over-pronation by recognize all types of wrong correlation which deviate from an ideal golden pattern over a threshold. Thus, the system needs the following components: 1) A golden data set, serving as reference, which contains correlation information from correct motions. 2) Real-time running data which is collected directly from uLeaps. 3) Algorithms that can precisely extract all the existing correlations from both golden data and real-time data. 4) Comparison modules that compare real-time correlations with reference (golden) correlations. 5) An optimized configuration of the threshold that can be used to judge the degree of improperness.

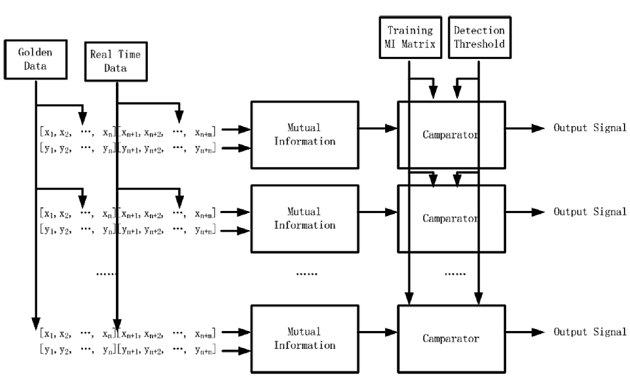


**Figure 4: Correlation and mutual information system diagram.**

The Correlation and Mutual Information system diagram is shown in Figure 4. Correlation and mutual information [11] are both necessary to determine behavior. The inputs are golden data, golden matrix and real-time data. For each 250 samples of real-time data, we append them to the golden data, calculate the MI matrix and compare it with the golden matrix and finally generate the output matrix. Thus, the time resolution of our system is about 4 seconds, which means the system can detect wrong correlations for every 4 seconds in running.

### *4.3.1 Correlations In Running*

We should first take a look at the real correlation in running to check linearity. To check the correlation of two random variables, we plot two measured data in 2-D plane, as seen in Figure 5. Clearly, the correlation in running is non-linear and sometimes difficult to map to any well-known functions. Therefore, we should choose an algorithm which can detect a general and non-linear dependency. Mutual information can be a very powerful tool in this case.

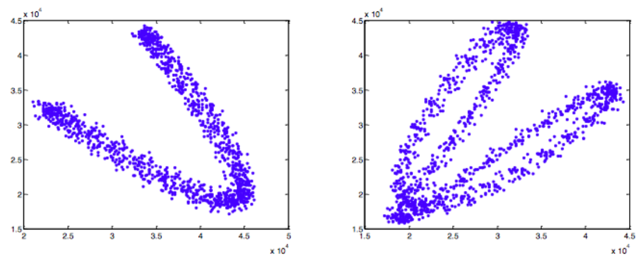

**Figure 5: Left: Correlation of left arm vs right arm. Right: Correlation of right arm vs right leg.**

### *4.3.2 Mutual Information*

The mutual information of two random variables is a measurement of the mutual dependence of two variables [7]. The most common measurement unit is "bit", using base 2 logarithms. Mutual information can be expressed as I(X;Y) = H(X,Y) - H(X|Y) - H(Y|X), where H(X|Y) and H(Y|X) are the conditional entropies, and H(X,Y) is the joint entropy of X and Y. Since H(X)>H(X|Y), the expression is consistent with the non-negativity property stated above.

### *4.3.3 Data Structure*

The input data structure is shown in the Figure 6. Each uLeap sensor has 6 channels of data. The first 3 channels represent the acceleration in X, Y, Z axis, respectively. The last 3 channels represent angle rate in X, Y, Z axis. In total, we have 30 channels of data from 5 laps, in the order of left arm, right arm, waist, left leg and right leg.

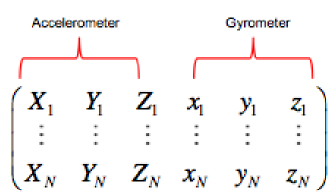


**Figure 6: Input data structure for arms, legs and waist.**

Each channel of data can be regarded as the measured data of random variables. Thus, each pair of two channels has different correlations to be examined. To calculate the correlation in matrix format, we use a 30x30 correlation matrix which includes 435 cross correlations symmetrically and 30 self-correlations in the diagonal line (30*30 = 435*2 + 30). The correlation matrix I(x,y) is shown in Fig 7. Each element inside is the mutual information of two channels of symmetric data, I(x,y) = I(y,x). The numbers in the diagonal are self-correlated, I(x,x) = 1.

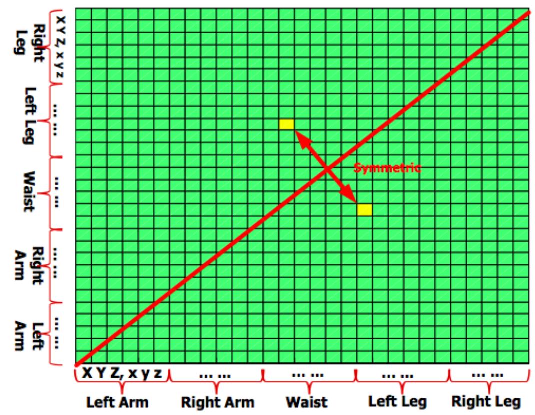


**Figure 7: Illustration of correlation matrix.**

### *4.3.4 Filter Selection*

As the running frequency of human is about 1-3 Hz, we decide to use a linear-phase FIR low pass filter. The configurations of the FIR filter are: $F_{pass}$ = 3Hz; $F_{stop}$ = 5Hz; $A_{pass}$ = 0.1dB; $A_{stop}$ = 90dB.

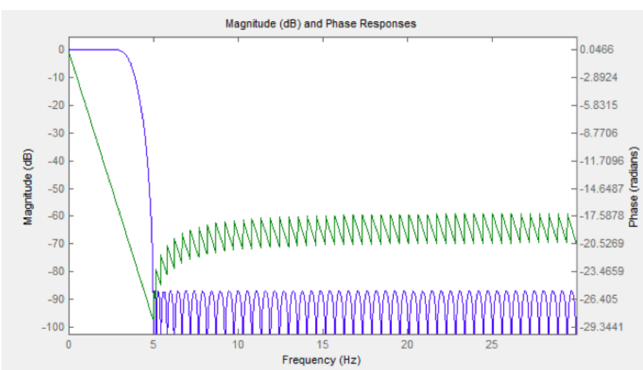


**Figure 8: Magnitude and frequency response of FIR filter.**

The magnitude and frequency response of the FIR filter is shown in Figure 8. Figure 9 shows the correlation pattern of raw data and filtered data. The high frequency noise degrades the quality of the data and the filter improves the data quality by removing the noise.

### *4.3.5 Data Quantization*

In digital systems, it is a simple way to quantize the data to $2^d$ by selecting the word length. Originally the data is quantized to 1 (d = 0) and has an entropy of 12-15. The higher the d is, the smaller the entropy of the data can be. In order to minimize the entropy of data, we should choose quantization number as high as possible. However, another effect of quantization is to introduce quantization noise. Thus, the quantization number is limited by the acceptable maximum quantization noise. Table 1 summarizes the detailed quantization effects. By choosing d = 7, we reduce the

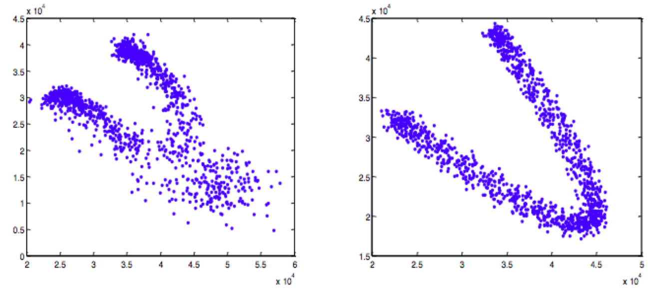

**Figure 9: Correlation plot of raw data (Left) and filtered data (Right).**

entropy of the data from 12 to 5.74, reduce possible values from 4096 to 53 and also reduce the computational complexity. In this configuration, the quantized data can still perfectly represent the clear butterfly shape.

| d | Entropy of data | N # of possible values | M>3N (# of samples) | T time interval (s) | SNR (dB) |
|---|---|---|---|---|---|
| 3 | 9.57 | 760 | 2280 | 38.00 | 82.53 |
| 4 | 8.87 | 468 | 1404 | 23.39 | 76.53 |
| 5 | 7.71 | 209 | 628 | 10.47 | 70.48 |
| 6 | 6.73 | 106 | 318 | 5.31 | 64.54 |
| 7 | 5.74 | 53 | 160 | 2.67 | 58.48 |
| 8 | 4.75 | 27 | 81 | 1.35 | 52.44 |
| 9 | 3.77 | 14 | 41 | 0.68 | 46.49 |
| 10 | 2.83 | 7 | 21 | 0.36 | 40.43 |

**Table 1: Summary of quantization effect.**

## 4.4 Feedback

### *4.4.1 Graphical Feedback*

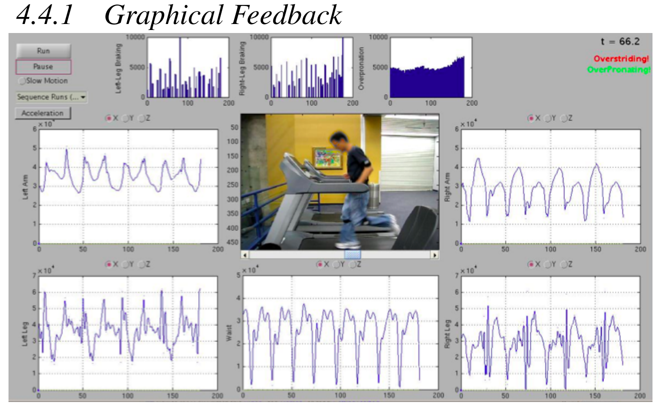


**Figure 10: Graphical user interface which displays acceleration waveforms with synchronized video.**

Figure 10 presents acceleration plots for the left arm, right arm, left leg, right leg, and waist. The user clicks radio buttons to select which axes to display for each plot. Additionally, the user can watch the video which is synchronized with the waveforms. It helps the user to see which motions are improper. The plots toward the top of GUI are the braking and over-pronation metrics as described previously in the signal processing section. The top right portion of GUI displays messages which tell the user if he/she is over-striding or over-pronating. The correlative feedback GUI is similar, but contains the golden mutual information matrix, difference matrix, and text describes which correlations deviate from the golden pattern.

### 4.4.2 *Real-Time Sensational Feedback*

The sensational feedback can inform the user of improper running behavior in realtime. Whenever the runner shows an improper motion, a signal is sent to the Microleap2 device to trigger vibrator motor, on the body part where incorrect movement exhibits. The high level design of the system is shown in Figure 11.

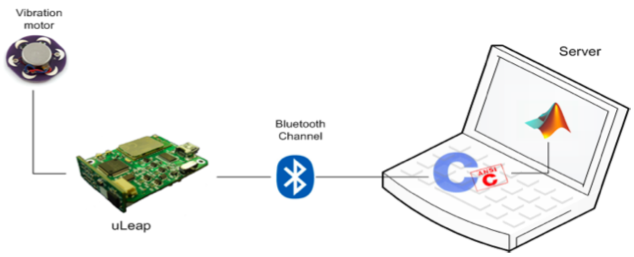


**Figure 11: System diagram for the Sensational Feedback.**

## 5. EVALUATION

### 5.1 Experiment Setup

The feedback system is tested against datasets including normal running, over-striding, and over-pronating. Initially, runners run for two minutes performing each of the three activities. The first test is to run detection algorithms on each set. Afterwards, we test one dataset include all three motions. A successful system should differentiate all of the motions in the same data set and trigger the vibration during the over-striding and over-promoting motions.

Before using the mutual information algorithm, we need to assess the reliability of the outputs. We first recognize whether there is an improper behavior in the running pattern, and then identify the type of behavior. One of the outputs from this correlation algorithm is a global 30x30 matrix which depicts all possible correlation combinations. We receive 30 different channels of output from five uLeaps on arms, legs and waist, as each uLeap sensor has six sensor data channels. A 30x30 golden matrix is taken from an ideal subset of proper running data and serves as the baseline. Then, we created other 30x30 mutual information matrices derived from running with known improper behaviors, and then subtracted these mutual information matrices from the golden matrix. We set a threshold which is manually found in experiment, and translate the differences between the two matrices into a set of threshold matrices. In these threshold matrices, black (0) element indicates no threshold violation and white (1) indicates a threshold violation (i.e. correlation error). The threshold matrix allows a clearer visual interpretation of the matrix.

We test two types of behaviors, over-striding and over-pronation. After the tests we have two different sets of threshold matrices for each improper behavior, and one set of threshold matrices corresponding to proper running. The threshold matrices would act as general error detection in the running pattern. Furthermore, we add up all the threshold matrices to obtain threshold sum matrices for each type of improper running behavior. These threshold sum matrices are then compared against an unknown 30x30 threshold matrix exhibiting either over-striding and over-pronation. Using the threshold matrices, this method can detect the type of improper behavior.

As mentioned before, the 30x30 matrix is used as a global view of the running data. For a more localized perspective, we produce a second correlation output, the scatterplot. This is basically the individual plots of each element in the 30x30 matrix. For example, regarding the left leg Z-axis and the right leg Z-axis data, the output is a 2D plot, in which the X-axis is the left leg's Z-axis accelerometer data and the Y-axis is the right leg's Z-axis accelerometer data. Using a scatterplot, shapes can be extracted from the plots which match particular running motions. This type of detection is more complicated to implement automatically, but it is more reliable than the first method. Furthermore, the scatterplots can be better interpret physically than the 30x30 matrix, and user can read that visualized output more easily. Thus, it is a more fine-grained method of finding correlations of motion between body parts of different running patterns.

### 5.2 Evaluation Results

First, we test if the threshold matrix is effective in detecting erroneous running patterns. In following examples, we apply a uniform threshold, 0.03, to the 30x30 difference matrix (subtracting golden matrix by correlation matrix) in Figure 12.

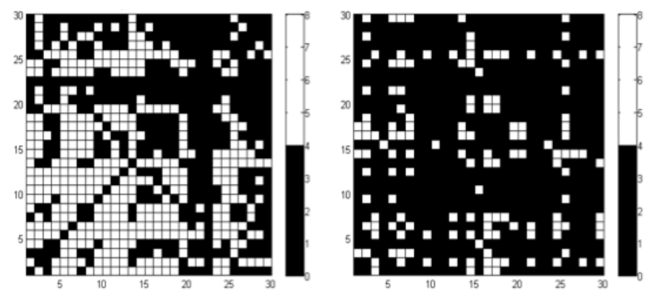

**Figure 12: Left: Over-pronate threshold. Right: Over-stride threshold.**

The threshold matrix successfully detects erroneous running patterns. The golden matrix is optimized to a particular person's running pattern. However, the golden matrix among users can be different, and we may get drastically different results by using different persons' golden matrices. One example is shown in Figure 13. In this section, we will put less attention on adapting golden data across different persons. In Figure 13, the maximum difference is 0.15, much greater than the 0.03 threshold. We will discuss the discrepancy in next section.

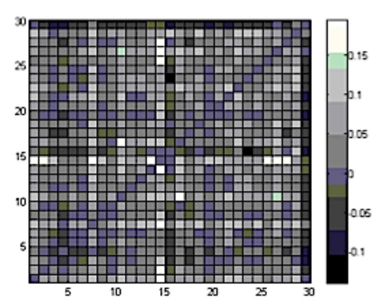

**Figure 13: Golden Matrix subtracted by proper running matrix of one subject.**

In the second test, we examine if the threshold sum matrix makes a successful distinguish between one wrong running behavior and another. We create two different threshold sum matrices for over-striding and over-pronation. These threshold sum matrices, like probabilistic maps, indicate the most probable location of threshold violation. We take a threshold matrix of one possible improper running behaviors. Then we normalize it to each threshold matrix and calculate the differences between it and each matrix. The overall magnitude of the difference matrix gives the likelihood to match that behavior. In Figure 14, the example displays threshold difference matrices in black-and-white for clearer interpretation.

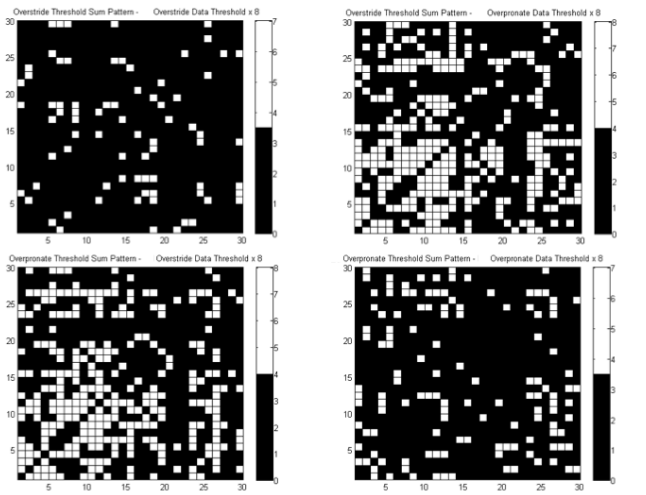


**Figure 14: Difference between threshold matrices. Top-left: over-stride threshold sum - over-stride threshold data; Top-right: over-stride threshold sum - over-pronate threshold data; Bottom-left: over-pronate threshold sum - over-stride threshold data; Bottom-right: over-pronate threshold sum - over-stride threshold data.**

The difference between threshold matrices and threshold sum probabilities can distinguish one improper behavior from another, as shown in Figure 14. In the left column, the over-stride and the over-pronation threshold sum probability are respectively compared against an over-stride threshold matrix. The magnitude of the discrepancy clearly indicates that the test data set represents over-striding behavior. Similarly, the right column shows the over-stride and over-pronation threshold sum probability matrices compared against an over-pronation threshold matrix. Again, the discrepancy magnitude correctly shows that the behavior is over-pronation.

In the last test, we examine scatterplots of the individual elements, as shown in Figure 15. We try to find how effective they are in distinguishing running behavior. These data exhibit distinct patterns based on the type of running behavior present in the data set. The blue points represent the golden data, a proper running form. Over-stride data is shown in red, and over-pronation data is represented in green. When the mutual information value in the 30x30 matrix is reasonably high, these scatterplots produce patterns exist in the golden data. In this case, matching the curve and shape of the scatterplot is helpful in improper behavior detection and behavior type identification.

# 6. DISCUSSION

## 6.1 GUI and Sensational Feedback

Overall, we and our participants are quite pleased with GUI and real-time feedback mechanisms. Our system makes correct detection when the users try to exhibit over-pronation and over-striding motions in purpose. For some runners, the feedback mechanism is

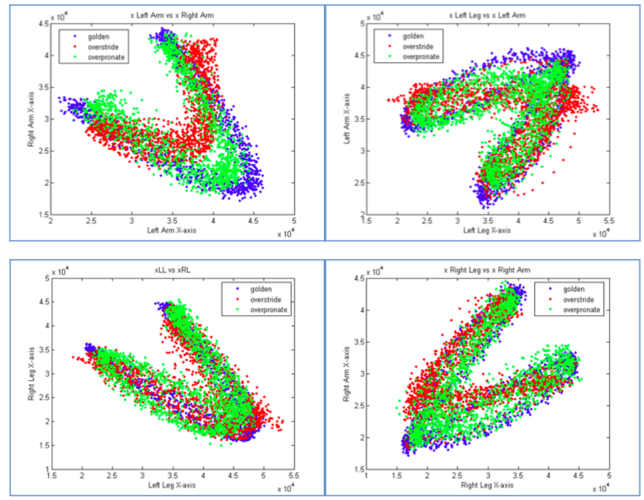


**Figure 15: Golden Matrix of Participant E Subtracted by Proper Running Matrix of Participant R.**

not triggered in some cases. However, when we watch the video and analyze, we find the discrepancy happens when the individuals involuntarily recover their normal running motion rather than keeping doing the improper running motions in whole experiment. One interesting note is that we may also detect improper motions within the participants who try to run normally. For example, during participant A's normal running, he triggers the over-striding mechanism on his right foot. From his video, we find he does land harder on his right foot than left foot time after time. In this case, he actually exhibits a braking force and consequently exerts strong force on his leg. Additionally, when participant S runs, he triggers the over-pronation feedback. After analyzing the video, it does appear that he is over-pronating. participant S also has flat feet, which makes him more naturally inclined to over-pronate. In the future, we would like to consult with an expert runner to determine the effectiveness of our feedback mechanisms.

One additional comment on the over-striding mechanism is that it does not directly determine if the user is over-striding. Instead, it computes the braking motion, a side effect from over-striding. Regardless of whether the user is over-striding, creating a braking force is harmful to the runner's body. This classification of over-striding can be extended to over-braking in the future.

## 6.2 Mutual Information

The mutual information algorithm works well in detecting and identifying problematic running behaviors. The ideal golden data is significant in the algorithm, since it works as a baseline. Because the data is not taken from professional runners, the golden data is not exactly the ideal running pattern. The concept of ideal running is not trivial, since different body types and different running styles can all have their own distinct proper running behaviors. The difficulty to establish an ideal running pattern contributes to the errors in our design. The feasibility of using our design depends on the ability of our input golden data to generalize to different running behaviors.

If the golden data fits proper running sufficiently, then improper behavior detection, in this case over-striding and over-pronation, can be detected easily. Using fitted lines or shapes (Hough transform) on the scatterplot is the best method of individual error detection, because deviation from the ideal running data's shape will immediately trigger an error. The shape of the deviation can then be analyzed with the golden data to detect the type of improper behavior, since each behavior has a distinct shape attributed to the correlated movement between each body part.

The threshold matrix also works well in behavior detection. Threshold sum matrices are helpful in distinguishing improper running behavior, but may not ensure one hundred percent accuracy. Based on closer analysis of the threshold matrix, several elements already have relatively low mutual information values in the golden data. A low mutual information value indicates that the data cannot confidently exhibit a particular pattern. When these seemingly random patterns in the golden data are matched with non-ideal data, the differences between the two mutual information values can vary more than the difference between an element of a distinct pattern and high correlation value. Therefore, the actual threshold value should be mutable with the mutual information value of the golden data. A higher value with a distinct pattern should be subjugated to a lower, tighter difference threshold, and a lower mutual information value with a random pattern should have a larger, looser difference threshold. Having a mutable threshold value will noticeably increase the accuracy and enhance the matching with the corresponding localized scatterplot. Fortunately, even with a uniform threshold, our algorithm still works great in detecting errors and identifying the improper running behaviors.

# 7. CONCLUSION

In this research, we develop a system which can detect improper running patterns using wearable sensors, and send graphical and vibration feedback to users. During our experiment, our system successfully detects over-striding and over-pronation motions when participants deliberately do so. Our system also correctly detect wrong motion when the participants try to run normally but involuntarily present improper motion. Afterwards, we confirm our detection based on video analysis. Moreover, we find the threshold matrix and scatterplot work well to identify improper running behaviors. After extended experiments with more subjects, we hope to deploy our system in school gyms and fitness club. Thus, a growing number of people can be noticed when they run with improper behaviors. Our system can help them correct running pose as soon as possible and avoid health issues due to these improper motion.

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