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A Review on Applied Machine learning in Wearable Technology and its Applications

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Abstract- Wearable technology has added a whole new dimension to already rich field of personal gadgets. It was the mobile phone which truly made gadgets personal. With so many services built around mobile phones, the market has opened up for a whole new personalization experience involving wearable technology. The fabric sensors that sense stretch, pressure, bend and even the direction of bracing on the body are now combined with wearable microcontrollers such as flora and lily pad. The connections between them are being made from conductive threads which curves along with the fabric. In this paper we will take a peek as to how different teams have applied the rich knowledge of wearable technologies to achieve their goals.

***Index Terms*—Wearable, Smart Fabrics, Body Area Network, sensors, Accelerometers, SAT (Sensor Activation Table)**

1. INTRODUCTION

An **E-textile** also known as smart garments or smart textiles are a class of fabric in which all the electronics and interconnections are woven onto the fabric itself and can interact with the environment and there is an elimination of wires and hard and complex electronic components. . The Fabric sensors are called as smart because it sense and react to environmental conditions or stimuli, such as those from mechanical, thermal, chemical, electrical, magnetic or other sources. The smart textiles are integrated in almost all the fields of applied sciences such as electronics, material science, optical fiber, organic chemistry, artificial-intelligence, Biotechnology, aviation hydraulics, telecommunication etc. In this era the smart textiles also referred as tex-tronics, which means the production of intelligent textiles materials incorporated with microchips, microprocessors or active sensory micro devices. Miniaturization of electronic components made it possible to create smaller and smaller sensors which can be worn all the time. The tex-tronics consist of four main components:
The first is the textile sensors like pressure, stretch, accelerometer etc. which is used to monitor any physiological variable or any other variables like heart or breathing rate. The second component is a family of conductive elastic yarns, which are building blocks in for example sensors and interconnects. These sensors consist of conductive nano-composite elastomeric polymers that exhibit changes in electrical conductivity as the material is stretched or under some deformation. The last group of components is conductive ribbon that attach to standard electronic connectors.

But the question arises how to incorporate all the sensors into the clothing and make it smart textiles. The figure 1 shows the steps for incorporating smartness into the clothing

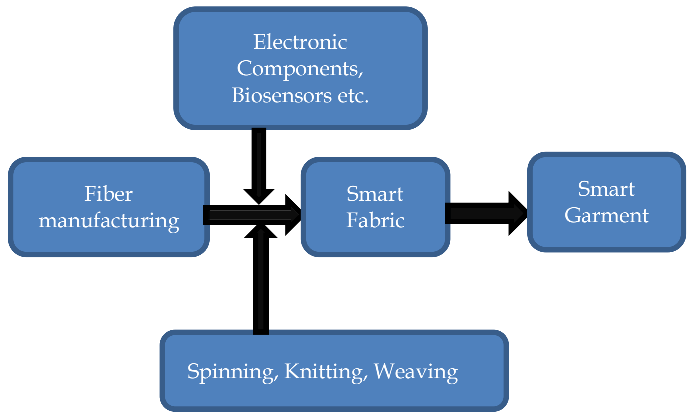


Figure 1: Fiber to Smart Fabric

The number and the variety of smart textiles and wearable devices has increased significantly over the past few years, as they provide health monitoring, human comfort and day to day monitoring of the user activities. Smart textiles are not restricted to apparels and clothing but also extended in many other applications like robotics, medicines, automobiles, surgery etc. The importance of these materials is so intense that they act as saving material in the combat zone for example in the military battleground the smart garment can change color to produce camaflogue effect for protection from enemy. It is also widespread in many applications like:

- Airplanes (e.g. in manufacture of flaps found in aircraft wings)
- Space research (e.g. special spacesuits designed for astronauts)
- Comfort wears (e.g. fabrics which can maintain body temperature)
- Sports (e.g. fabrics which can make athletes feel comfortable even in stretched body conditions)
- Biomedical field (e.g. measuring physiological parameters like breathing rate, respiration rate, ECG, muscle activity etc.)

The advent of technology and the ease of the availability of smart sensors makes it easy for monitoring and logging of the life activities. People are keeping track of everything from the number of calories burnt in a day to receiving a phone call by touching the garment as implemented in the jacquard project which is a joint venture by Google and Levis The smart textiles can be made by incorporating smart materials (piezoelectric, Thermoelectric etc.) electronic sensors and communication equipment into the many conductive fibers and yarns. Electronic circuits can be built entirely using textiles to distribute data, power transmission and storage etc. The interconnection or communication between different components making up a smart textile system is mainly realized by electro-conductive yarns woven into textiles [42], to form a bus structure (Figures 2).

Figure 2: Electro conductive ribbon sample [42] Reprinted from http://www.titvgreiz.de, with permission of TITV Greiz.

In this paper we discuss about the different research projects on e-textiles and classification of different types of fabric sensors and different sensor locations for capture human motion and the sensor data which is collected from the different sensors to be used further for the classification of human activity using Machine learning.

3. CLASSIFICATION OF SENSORS

- **Pressure Sensor**

The sensor is based on the Piezo-resistive effect, where the electrical resistance of a material changes under mechanical pressure. This sensor can be created using velostat as a semi Permeable layer between two pieces of conductive fabric to create pressure on it.

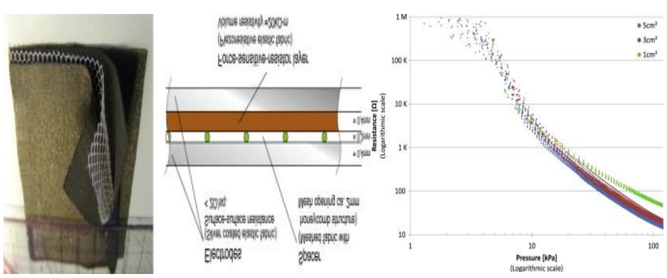


Figure 3: The construction of a fabric pressure sensor with three layers (Reference 26)

- **Stretch Sensor**

This sensor shows Piezo-resistive properties when deformation is applied that depends on the stretching of the fabric. As the stretch sensor is stretched the resistance gradually increases or decreases. These sensors are made from a conductive fabric. It is possible to manufacture them from a non-conductive fabric depending on the specific application needs. It is used to monitor human body motion and shape.

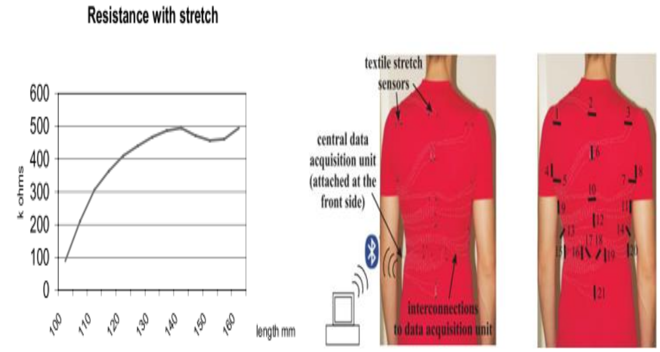


Figure 4: Sensor for measuring stretch [45].

- **Bend Sensor**

This bend sensor reacts (decreases in resistance) to pressure, not specifically to bend. But because it is sandwiched between two layers of neoprene (rather sturdy fabric), pressure is exerted while bending, thus allowing one to measure bend (angle) via pressure. It is used for measuring the bend of human joints when attached to the body. It is sensitive enough to register even slight bend and has a large enough range to still get information when the limbs are fully bent.

Figure 5: A textile bend sensor created is using conductive fabric and neoprene

- A/M/G Sensor

It is a high precision 3-axis Accelerometer, Compass sensor, in which a classic 3-axis accelerometer, tells which direction is down towards the Earth (by measuring gravity) or how fast the board is accelerating in 3D space. The other is a magnetometer that can sense where the strongest magnetic force is coming from, generally used to detect magnetic north.

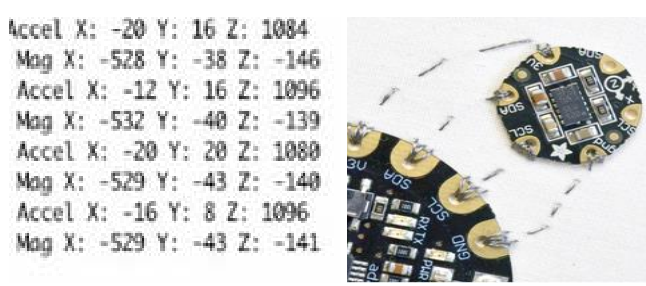


Figure 6: Flora A/M/G Fabric sensor

- BIO Sensors

Wearable monitoring devices allows the continuous monitoring of physiological parameters and it also temporarily store the physiological data and then periodically upload the data to the server and send the data to the doctor for the diagnosis of the disease. There are number of wearable biosensors are available today such as:

- Helmet for the treatment of the depression
- Prevention of bed sores by smart clothing
- Smart clothing for premature babies
- Smart shoes
- Measuring stress with t-shirt
- Smart clothing to monitor children health status
- Heart health by smart vest
- Smart socks
- Digital clothing that measures mental conditions.

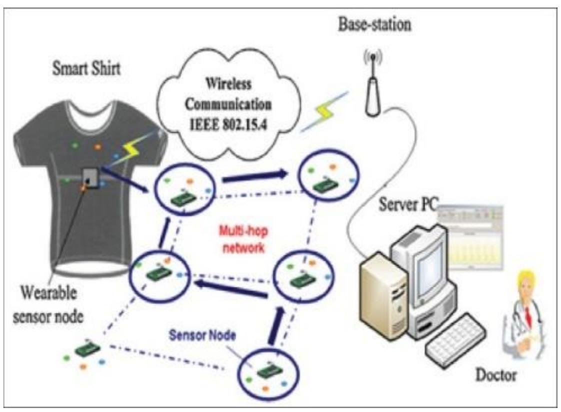
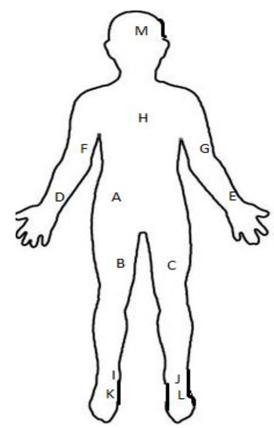


Figure 7: System Architecture with Smart shirt

4. WEARABLE TECHNOLOGY FOR HUMAN POSTURE DETECTION

Wearable devices have gained attention over the past few years by the various industries for everyday use. Technological developments have assisted athletes, military soldiers and physicians to track functional movements, and measure bio-vital markers to maximize performance and public safety while minimizing the potential for accidents [1]. Using wearable technology Maria Cornacchia et al. [2] had done survey on activity detection and classification covered a variety of sensing methods, including accelerometer, gyroscope, pressure sensors, stretch, bend, twist sensors and camera systems. In addition to the type of sensors and type of activities classified, they provide details on the body area network where the devices may be placed or mounted on the human body in a particular position. There is a large body of work using A/M/G sensors for activity classification. Accelerometer-based systems have been proposed for fall detection [3-7]. There are systems using single device accelerometer-based system [8-11] and those fusing several sensors [12-13] to detect ambulatory-type activities. Others are performing posture recognition [14].

Many activity classification algorithms have been predicted for Android or other smartphone platforms using only accelerometer data [15–19]. Accelerometer-based systems are used in [19] and [20] to distinguish between walking, running, cycling, and driving. Accelerometers have also been used in the activity classification of workout [21]. Various algorithms have been suggested by various authors for the identification of human posture detection Stephen et al. [22] and W. Tang [23] has offered different classification schemes and feature extraction methods to identify the different activities from arrange of different datasets and compared the classification accuracy for each feature set across different combinations of three different accelerometer placements. Other techniques also have been used for the classification of data from the wearable sensors like support vector machine, hidden Markov model, Random Forest and artificial neural network to recognize different body activities [24-27]. Using above all the methods the performance have been achieved till 95% and performance can be increased by using other features, such as age, weight, statistics of acceleration, physiological measurements of the subject, during a specific activity etc. can also be taken into consideration [24-28]. Various other techniques have used to automatically classify human body postures like Singular Value Decomposition (SVD), Multiscale Entropy, Fuzzy Logic, Naïve Bayes etc. [29-31].The Figure 8 shows the placements of sensors employed on the human body for the detection of human motion in the survey. As discussed in [31] activity classification vary from person to person according to its BMI. Using only accelerometer data is not sufficient for the activity classification, many others sensors to be needed for the more accuracy.



A-Waist, B- Right Thigh, C-Left Thigh, D-Right wrist, E-Left Wrist, F-Right Arm, G-Left Arm, H-Chest, I-Right Ankle, J-left Ankle, K-Right foot, L-Left Foot, M-Head

Figure 8: Body Area Network: Sensor Locations Employed

4.1 METHODS FOR THE CLASSIFICATION OF HUMAN ACTIVITY DATA

The most important characteristic to be considered in building a system for recognition or classification of human physical activity is the choice of sensors. Wearable sensors should be small and light weight and comfortably to be worn. In the previous sections we have discussed about the various sensors which can be used and implement machine learning algorithms in it. Various papers have used accelerometer sensors [11-25] for detecting the ambulatory activities. The data which is collected from the sensors can be used for applying various machine learning algorithms. Every machine learning workflow begins with three questions: what kind of data to be used, what insights do you want to get from it and how and where those insights be applied. The answers to these questions help to understand what kind of learning to be used whether it's a supervised or unsupervised learning.

Few steps to be followed for testing and training the data taken from the sensors as shown in Figure 8

Step 1: Load the data

To load data from the sensors we do the physical activities like sitting, standing, walking after the sensors are worn. Repeat the steps until we have enough data for each activity for training. Compile the data in Sensor Activation Table or in a Matrix form and do the necessary changes using different techniques to improve the accuracy. Figure 9 shows the steps to be followed for the data classification.

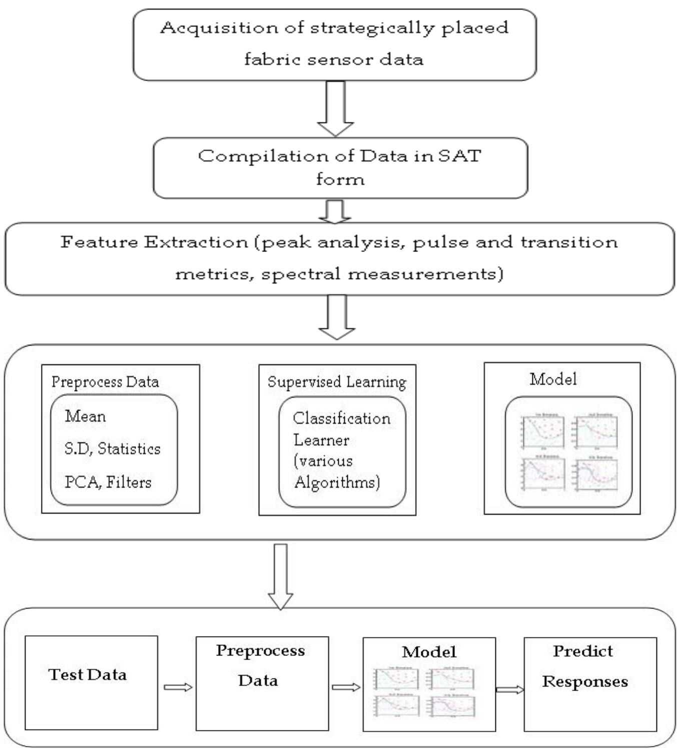


Figure 9: Flow Diagram for the data classification

We store the labeled data sets in a text file. Machine learning algorithms aren't smart enough to tell the difference between noise and valuable information. Before using the data for training, we need to make sure it's clean and complete.

Step 2: Pre-process data

For the pre-processing, we check for outliers- data points that lie outside the rest of the data and also for missing values but ignoring the missing values will reduce the size of the data. Divide the data-set into two parts and part of the data will be used for testing and rest of the data for training to build the models also known as cross validation technique.

Step 3: Feature Selection and Extraction

This method turns the raw data into information that machine learning can use them. Table 3 shows the feature extraction methods used for various postures. Allen et al [11] have used feature vectors which include the signals from all three axes of both the gravity and body acceleration components. Most of the studies have used frequency-derived features employing an FFT or parameters such as averages or correlations calculated over long time-windows [23]. Although the choice of features is an important factor, and different researchers may pursue different approaches for their identification and computation [21].Simple statistical methods are also used for the activity detection like variance, Standard Deviation, Mean value, Correlation etc. [17, 22, 25]

Step 4: Build and Train the model

Need to choose the learning approach for building a model. Different authors have used different classifiers for the human activity classification. Selecting a machine learning algorithm is a trial and error process. It's also a trade-off between specific characteristics of the algorithms, such as:

- Training Speed
- Memory usage
- Accuracy

Many algorithms have been used for the posture detection Naïve Bayes, k-NN, SVM, Decision Tree, HMM, GMM etc.

K-Nearest Neighbor (k-NN) classifiers, work directly on the geometrical distances between feature vectors from different classes whereas SVM classifies the data by finding the linear decision boundary that separates all data points of one class from those of the other class. Naive Bayes is a probabilistic technique that classifies new data based on the highest probability of its belonging to a particular class. Finally the ANN is a model and feature based approach on specification, model checking and testing. Table 2 summarizes the information which includes, as for sensor location, selected features, number of activities and tested subjects; accuracy of classification. It observed that SVM shows the maximum accuracy for the data classification.

6. CONCLUSION

The information presented in this review paper is just the tip of the iceberg. There are much complex projects being undertaken which would require an entire paper to discuss. The Google and Nike's joint venture project named jacquard is one such example. The applications of wearable technology combined with machine learning is the most challenging and yet promising field of study. Training a machine to classify itself has inherent challenges when it comes to quality of data involved. Above this, the analog data produced by fabric sensors and their sensitivity to different changes could bring down the quality of data. It will be technically challenging to handle both complexity in a single system and orchestrate controlled input and output in order to achieve a well-defined goal. The combination of fabric sensors, wearable computers and machine learning is going to open up a whole new field of analysis which can enrich lives.

Table 2: Related Work for human posture detection using various sensors

Reference	Placement of Sensor	Features	Detected Activities	Sensor Type	No. of Sensors	No. of Subjects	Approach	Accuracy
Allen et al [33]	Waist	Body Acceleration Components, Gravity Components,	Sitting, standing ,lying) sit-to-stand, stand-to-sit, and walking) etc.	Accelerometer	3	6	GMM	91.3%
Littman et al [34]	NA	Standard deviation, Energy distribution Correlation coefficients	Walking, sitting, watching TV, running, eating, reading etc.	Accelerometer	5	NA	Naive Bayesian k-NN SVM Binary decision	Approx. 90-98%
Seon-Woo Lee et al [36]	Waist, Thighs	Raw data Standard deviation Derivative	Sitting, Standing, & Walking behaviour	2D acc. gyro, compass	3	8	Threshold based	92-95%
Enrique Garcia et al [35]	Wrist	State Transition Probability Distribution	Long-term activities (Shopping, Showering, Dinner, Working, etc.	Wrist Watch Accelerometer	1	5	Hidden Markov Models, Conditional Random Fields	65-75%
Wenlong Tang et al [23]	Sole &Heel	Mean value, Standard Deviation, entropy	Sit, Stand, Jog, Cycle	Pressure Sensor, Acce.	5	9	SVM, MLP	96-98%
Attalah et al [38]	Waist, Thighs	Mean Square Error	Sitting ,lying, standing and walking speed	Accelerometers	3	5	Extended Kalman Filtering	80-92%
Mannini et al [37]	Waist, Arms, legs	Dynamic time wrapping	Sitting, standing, and walking behaviour	Acc., gyro, Magnetometers	4 or more	8	HMM	92-98%
Bao et al [39]	4 limbs and the right hip	Standard deviation Energy distribution Entropy Correlation coefficients	Walking, sitting, running, bicycling. Stretching, Lying down and relaxing	2D accelerometer	5	20	Naive Bayesian k-NN Binary decision ANN	84%
Kristof Van et al [40]	Connected a pair of pants with accelerometers to a laptop	Standard deviation FFT coefficients Derivative	Sitting, Standing, Descending stairs, walking etc.	2D Accelerometer	1	NA	ANN	42-96%

Chamroukhi et al [24]	Chest, Thigh, Ankle	Probability	Stairs, Ascent and Descent, Walking, Standing up, Sitting on ground etc.	Accelerometer	3	10	HMM, K-NN, Naïve-Bayes, SVM	80-95%
Edward S [41s]	heel, heads of metatarsal bones, and the hallux	Signal mean, variance, entropy, energy, pairwise axis correlation	Sitting ,standing postures, walking, running, stair ascent/descent etc.	Pressure Sensor and Accelerometer	5	9	SVM	95.2%
Yuchuan Wu a et al [49]	Waist	Discrete Wavelet Transform & IDWT	standing, jumping, sitting- down, walking, running, and falling performed	Tri-axial Accelerometer	1	13	Wavelet-based principle component analysis, SVM	95.25 and 94.87%
Congcong et al [50]	Cushion Seat	N/A	Proper Sitting, Lean Left , Lean Right, Learn Forward, Lean Backward	Pressure Sensor Array	12	4	Decision Tree (J48), (SVM), (MLP), Naive Bayes, and (k-NN)	99.47%
Roland et al [51]	Chair	Median Values	Different sitting positions	Force and Acceleration Sensors	16	41	SVM, Neural Network, Random Forest	81% and 98%
Pierluig et al [52]	N/A	Mean Value, RMS Value, Standard Deviation	Stairs, Walking, Talking, Standing, Working PC	Bi-axial Accelerometer	5	14	Random Forest	94%
Long Chen et al [53]	left thigh, right arm, right ankle and abdomen	Body Acceleration Components, Gravity Components	Sitting, Sitting Down, Standing , Standing up, Walking	Accelerometer	4	4	SVM, HMM, ANN	92-99%
Yuchuan Wu a et al [49]	Waist	Discrete Wavelet Transform & IDWT	standing, jumping, sitting- down, walking, running, and falling performed	Tri-axial Accelerometer	1	13	Wavelet-based principle component analysis, SVM	95.25 and 94.87%

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