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DNN based Approach for the Assessment of Elbow Flexion with Smart Textile Sensor

Maxence Bobin*, Hamdi Amroun*, Sabine Coquillart[†], Franck Bimbard*, Mehdi Ammi*

*LIMSI-CNRS

{maxence.bobin, hamdi.amroun, mehdi.ammi}@limsi.fr

[†]INRIA-LIG-UGA

{sabine.coquillart}@inria.fr

Abstract—This paper presents a new approach for monitoring the elbow flexion with a smart textile based on the piezo-resistive effect. The sensor is composed of a mix of conductive threads made of stainless steel fibers doped with metal particles and dielectric silk threads. The threads are arranged in a double braid structure to provide the best compromise between mechanical elasticity and sensor sensitivity. The sensor was integrated to a sweater to measure the joint angle of the elbow. In order to assess the angle in a robust and accurate way, we developed a static model for angle recognition based on a machine learning algorithm: a Deep Neural Network. The design process of the static model includes the data collection, the extraction of features and the choice of the best architecture for the Deep Neural Network. This approach allows to reach recognition accuracy between 76.9% and 83.66%. Finally, a comparative study has also been performed in order to compare the performances of our model with different algorithms such as SVM, NB and DT.

I. INTRODUCTION

Monitoring the human body activity continues to attract the interest of the scientific community in recent years. This area raises many challenges such as portability, usability or accuracy. The majority of human activity analysis uses smart objects like smartphones or smart watches. Although these platforms provide satisfactory results in terms of accuracy of physical activity recognition, they present problems in terms of portability and feasibility. For instance, the analysis of physical activity using a mobile phone can only be carried out if the phone is permanently held by the user. Indeed, it happens that the user drops it out of reach when he/she comes home for example, which further complicates the detection of physical activity using this kind of platforms. In addition, the data used in this work, although it provides good recognition accuracy in most cases, remains limited around the use of inertial unit sensors and sometimes audio data to capture the sound environmental impact assessment [1].

The use of classical sensors for human body monitoring, even integrated into garments, do not fit daily usages and do not support humidity or washing machine. As classical sensors are not designed for human body monitoring, the conception of electronic devices that are flexible and fit the human body presents a breakthrough in many areas of application such as occupational health, video games, virtual reality, teleoperation and health monitoring. New textile fabrics allow to create textile sensors at low cost based on different physics concepts

(piezoresistivity, piezoelectricity or piezocapacitive materials) that are compatible with manufacturing process and easy to use. These new kind of sensor can be integrated directly into a garment during the fabrication. However, these textile sensors present constraints on the collected data due to their constitution. The two main constraints of textile sensors data are the noise and the hysteresis. First, the noise comes from the friction between the thread fibers. During a stretching, friction holds the fibers back until the stretching force exceeds the friction coefficient which induces noise into the measured data. Second, textile sensors present hysteresis which is due to the friction between the fibers and the non-elasticity of the fibers. The textile sensors lead to create a new way to process collected data in order to go beyond these constraints.

This paper addresses the design and integration of a smart textile sensor into a sweater as well as the design of a new DNN based approach for the assessment of the elbow flexion with this sensor. A study has been carried out in order to find the best parameters for the DNN algorithm and a comparison with other algorithms has been performed.

II. RELATED WORK

Many researches focus on smart textile fabrics with piezo-resistive properties to create different kinds of sensors such as flexion, respiratory rate or pressure sensors and even electrocardiograms. There are three main approaches to design textile sensors: (1) knitting conductive thread, (2) dielectric material covered by piezo-resistive polymer and (3) superposition of layers with different electrical properties. The first approach consists in knitting conductive threads as a strip allowing to create flexion sensors based on the changes of resistivity during stretching [2]. The sensors are placed at specific places on the body to perform flexion tracking and posture detection by measuring knit strip resistivity. The more the strip is stretched, the more the resistivity increases. Other researches focus on developing respiratory rate sensors [3]. During breathing, the rib cage volume periodically increases and decreases. Measuring the evolution of knitted strip's resistance allows to monitor the respiratory rate.

The second approach is a coating process with polymer exploiting piezo-resistivity effect allows to design sensors with the same purposes. A dielectric material can be coated with

polymer that give to the material piezo-resistive properties. This technique is based on the strain gauge principle. Flexion sensors have been created with different materials such as carbon-loaded elastomer [4], foam coated with a thin layer of polypyrrole (PPy, a π -electron conjugated conducting polymer) [5] or jersey fabric composed of 86% polyester and 14% lycra with a solution of rubber containing micro disperse phases of carbon [6]. These sensors also allow to monitor the human body posture by placing the sensors on specific areas (shoulder, elbow, etc.). Other posture sensors are based on elastic threads coated with PPy or by a mixture of rubber and carbon [7]. Some of these sensors have been placed along the semicircumference of the rib cage and the abdomen to monitor the respiratory rate [4].

Finally, the third fabrication process is the superposition of different layers of piezo-resistive and dielectric materials. Flexion sensors have been developed with this technique such as a capacitive bend sensor with three layers : a first member having a comb-like portion of conductive material, a second one having the same design and a dielectric material between the conductive materials [8]. When the two conductive combs slide relative to one another, the capacitance increases from a maximum when the comb teeth are aligned, at least when the teeth of a comb are aligned with the spaces on the comb. The capacitance between the two comb patterns is therefore linearly proportional to the bending angle of the sensor for a range of bending angles. Other research highlighted the use of this technique to create pressure sensor [9] or respiratory rate sensor [10].

The emergence of Internet of Things (IoT) allows to use machine learning with common sensors in order to recognize human activities. Several works addressed this issue using different models: HMM [11], SVM, Naive Bayes Classifier [12] and Decision trees [13]. However, the approaches presented in these previous works are mostly not robust with low recognition rates and sometimes very consuming in terms of computation time and memory space. Deep Neural Networks (DNNs) are a promising alternative to these constraints. In fact, they were successfully applied for the classification of handwritten characters and gesture recognition [14]. Others works show very good human activity recognition performances using accelerometers [15]. However, the application of this kind of models requires a lot of memory space and computing time. This is due, among other things, to the non-selection of features to be input to the DNN for learning [16].

Most of the works interested in developing techniques to improve the recognition rate of the activity (machine learning algorithms) but very few works interested in finding the best descriptors to extract for the learning process such as Da Silva et al. who developed a system for recognizing activity using a smartwatch [17]. They extracted nineteen features using two techniques: Fisher Discriminant Ratio (FDR) and Principal Component Analysis (PCA). They used SVM to classify the extracted features and obtained a performance

of nearly 93% accuracy. He et al. focused on other types of features such as autoregressive feature [18]. They presented an autoregressive pattern to recognize human activity. These features were extracted for classification using SVM and obtained a classification performance of 92.25% accuracy. Other kinds of descriptors have been extracted such as Fast Fourier Transform (FFT) or Discrete Cosine Transform (DCT) such as He et al. who developed an activity recognition model based on a single accelerometer [19]. They opted to extract features with the DCT from input signals, used SVM for classification and reached an accuracy of 97.51%.

This paper presents a new approach for the assessment of elbow flexion with smart textile sensor using machine learning. This work focuses on the creation of a smart textile sensor for elbow flexion based on the piezo-resistive effect and the double bridle crochet structure. The sensor have been incorporated on a sweater. Then, the process of machine learning using a Deep Neural Network is presented. This machine learning algorithm allows to resolve the problems of noisy signals and hysteresis. Finally, a comparative study between our approach and other machine learning algorithms have been carried out.

III. THE PIEZO-RESISTIVE TEXTILE SENSOR

The piezo-resistive textile sensor is based on the use of electromechanical functional threads with two main properties: (1) the piezo-resistivity and (2) the electrical conductivity at the surface of the fibers. Piezo-resistivity allows variations in the electrical resistance of the wire when subjected to mechanical stress, particularly when the wire is stretched. This is an intrinsic property of the threads. The electrical conductivity at the surface of the fibers allow to use the number of contacts between fibers i.e. the whole structure of the sensor. Indeed, when the textile structure is not subjected to mechanical stress, the number of contacts between the wires is reduced, which gives a high electrical resistance of the textile structure. When the textile structure undergoes a stress of tensile or pressure type, the number of contacts between the wires increases which reduces the electrical resistance. This is an extrinsic property of the sensor. We decided to base the textile sensor on the double bridle crochet technique (See Figure 1) in order to improve the sensitivity of the sensor by using intrinsic and extrinsic properties of both threads and structure.

The textile sensor has a rectangle shape and a size of 20 cm by 5 cm. Each mesh has a size of 1 cm by 1 cm. The sensor is made of a mix of dielectric threads and conductive threads. The non-conductive thread is a silk thread used in classic sewing. The conductive thread is a stainless steel thread with a surface resistance of 28 Ω per feet.

The sensor was sew on a classic sweater (See Figure 2) with a silk thread in order to avoid external electric perturbations. The sleeve was reduced to fit closely the arm and avoid the sensor to move along the arm. Moreover, the more the sleeve fits the arm, the best the sensibility of the sensor is because

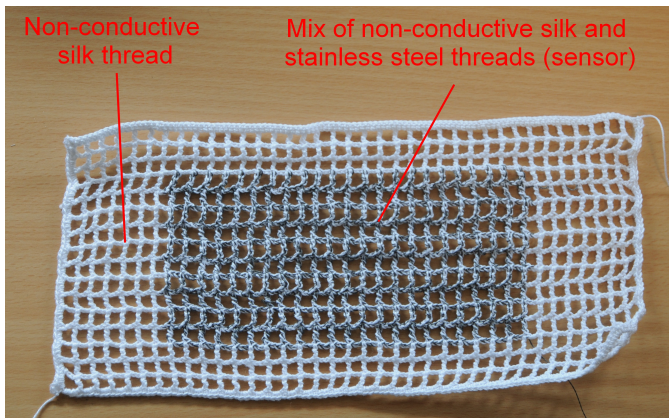


Fig. 1: Example of a textile sensor based on the crochet structure.

the sensor is more stretched during the elbow flexion.



Fig. 2: The piezo-resistive sensor integrated in the sweater.

The electronic system is based on the TinyDuino¹ platform which is a miniature open-source electronics platform based on the easy-to-use hardware and software Arduino platform. The TinyDuino Processor Board embeds the same Atmel Atmega328P microcontroller as on the Uno and support all the same signals (14 digital inputs/output pins and 6 analog inputs with a size of 20mm by 20mm). However, the TinyDuino Processor Board uses an 8MHz ceramic resonator instead of the 16MHz that the Uno uses. The TinyDuino is powered by a 3.7V and 140mAh battery. In order to measure the sensor electrical resistance, we developed an acquisition platform based on a tension divider bridge composed of a 10 Ω resistance and the textile sensor. A Bluetooth shield have been added to the TinyDuino in order to share data with a remote computer. The global architecture of the prototype is presented in the Figure 3.

Voltage measures are performed at the longitudinal extremities of the sensor via analog input. However, the data

¹<https://tinycircuits.com/pages/tinyduino-overview>

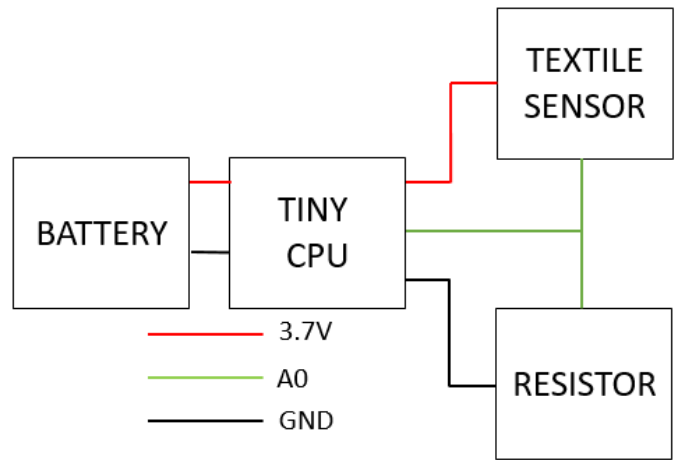


Fig. 3: Hardware architecture of the electronic system based on TinyDuino platform.

recorded during the monitoring of the sensor resistance over time presents noise and hysteresis. The figure 4 shows the collected signal from a real user performing an elbow flexion and extension. As we can see, some peaks appears just before a transition to another state. For example, for an elbow flexion from 0 to 90°, values instantly drop from 1.20 Ω to 0.90 Ω before rising to 1.30 Ω . Furthermore, hysteresis is very well exposed during the transition during flexion from max to 90°. The values retrieved from the sensor instantly drop from 2.20 Ω to 1.10 Ω . The values increase slowly to reach 1.40 Ω which correspond to the value after a transition from 0 to 90°. Moreover, values returned by the sensor depends on the corpulence of the user. Indeed, as the resistance of the sensor depends on the mechanical stretching, the size of the arm modify the range of values returned by the sensor.

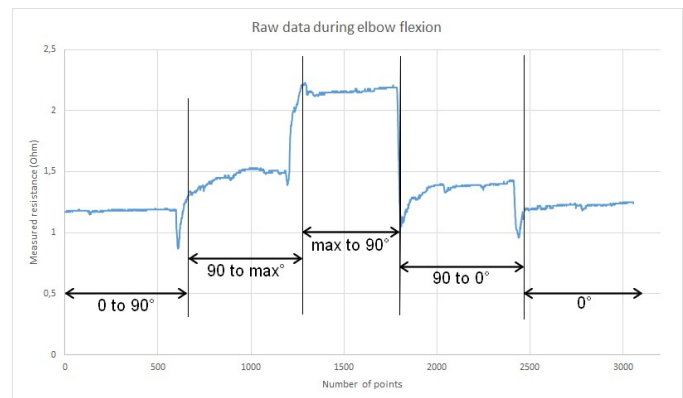


Fig. 4: Example of noise on raw data from textile sensor.

IV. DESIGN OF A STATIC MODEL FOR ANGLE RECOGNITION

In order to solve the problems mentioned above (noise, hysteresis and variation of the user's corpulence), a static model for angle recognition have been developed. The

creation of this model is divided in four steps:

- A. Data collection
- B. Extraction of a useful signal and merging of the descriptors
- C. Learning by a Deep Neural Network (DNN)
- D. Comparative study with other methods

A. Data collection

The experiment took place in a laboratory room. Ten participants were invited to perform five types of activities by wearing the garment described above. The activities consist of bending the arm to reach the specific configurations: (1) 0°, (2) 90°, (3) maximum bend angle, (4) 90° and (5) 0°. Each activity includes the transition towards the next one. The five activities are annotated as follow:

- (1) 0_90 : 20 sec at 0° and transition towards 90°
- (2) 90_max : 20 sec at 90° and transition towards max angle
- (3) max_90 : 20 sec at max angle and transition towards 90°
- (4) 90_0 : 20 sec at 90° and transition towards 0°
- (5) 0_0 : 20 sec at 0°

The data recordings were made at a sampling frequency of 30Hz via Wi-Fi and under controlled conditions. The simulated characteristics appear to be relevant and easily controllable.

B. Extraction of a useful signal and merging of the descriptors

1) *Extraction of a useful signal*: A de-noiser have been applied on the collected signals in order to suppress the noise generated during transitions from one activity to another. Then, the signals were segmented into multiple windows with equal durations (434 ms). The segmentation allows to extract stable and periodic signal.

2) *Merging descriptors*: Different descriptors, i.e. representative key points of a signal, exists in the literature to perform activity recognition. The following descriptors have been extracted according to several works which approved their effectiveness [1], [12], [20]:

1. The Discrete cosine transform (DCT-II). The DCT of a sample $X(n)$, $n=0, 1, (N-1)$ is given by:

$$X(0) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x(n) \quad (1)$$

$$X(k) = \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} x(n) \cos \frac{(2n+1)\pi k}{2N}, k = 1..(N-1) \quad (2)$$

2. The sum on the absolute values of FFT components:

$$S = \sum_{i=1}^M |C_i|^2 \quad (3)$$

where C_i is the i -th component of the signal of each labeled activity.

3. Entropy in the frequency domain:

$$T = \sum_{j=1}^{N-1} p(j) \log p(j) \quad (4)$$

where $p(j)$ is the propability distribution derived from the normalized FFT component using the following formula:

$$p(j) = \frac{|F_j|^2}{\sum_{j=1}^{N-1} |F_j|^2} \quad (5)$$

4. Signal Vector Magnitude (SVM) and Differential Signal Vector Magnitude (DSVM) metrics are similar to the norm as defined below:

$$SVM = \frac{1}{n} \sum_{i=1}^n \sqrt{x_i^2 + y_i^2 + z_i^2} \quad (6)$$

$$DSVM = \frac{1}{t} \left(\int_0^t \sum SVM' |dt \right) \quad (7)$$

Once the descriptors are computed, they have been concatenated to form a vector of size 61 (15 + 8 + 23 + 9 + 6) that regroup the advantages of each descriptor separately.

C. Learning by a Deep Neural Network

The Deep Neural Network (DNN) have been used as classifier model. Indeed, DNN is a non linear classification model very used in the past few years with a good efficiency. The resultant descriptor vector from concatenation is given as an input to the automatic learning algorithm. The outputs of the DNN correspond to the number of activities classes, i.e. 5.

The training of the DNN was carried out in four stages: (1) merging the descriptors of 13 frames, which included the center frame, the 6 preceding frames and the 6 succeeding frames. A 806 (61*13) dimensional descriptor vector have been therefore used as the DNN input, (2) normalization of the input data by subtracting the mean and dividing by the standard deviation, (3) pre-training of the model using a restricted Boltzmann machine (RBM) to set the appropriate initial parameters of the DNN with the normalized concatenated descriptors and (4) training of the DNN by fine-tuning by using back propagation algorithm with the labeled data signals. During the fine-tuning step, the DNN was trained at a fixed learning rate. After 25 epochs, we began to have the learning rate every half epoch.

1) *Choice of the best architecture*: In order to determine the best architecture corresponding to our data signals (i.e. number of hidden layers and number of neurons in each hidden layer), we propose to follow a methodology inspired by Chen et al. [21] with some modifications and considerations that allow to overcome the problem of over-fitting (learning by heart without generalization). At each step, neurons are added and the classification accuracy is calculated with the test set. The number of neurons retained in a hidden layer is determined when the accuracy of recognition stops increasing by adding

Nb of neurons \ Nb of layers	Nb of layers					
	1	2	3	4	5	6
100	0.26	0.32	0.38	0.44	0.47	0.19
150	0.29	0.38	0.46	0.49	0.56	0.22
250	0.33	0.59	0.51	0.55	0.62	0.17
350	0.34	0.6	0.63	0.67	0.66	0.11
450	0.29	0.62	0.69	0.7	0.67	0.07
550	0.28	0.44	0.62	0.62	0.73	0.07
650	0.27	0.40	0.53	0.61	0.75	0.07
750	0.25	0.34	0.48	0.50	0.79	0.04
900	0.22	0.29	0.44	0.48	0.55	0.03
950	0.22	0.29	0.39	0.41	0.53	0.02
1000	0.21	0.28	0.39	0.34	0.49	0.02

TABLE I: Learning outcomes according to the number of layers and number of neurons.

neurons. The next step was to do the same reasoning by adding hidden layers until the recognition accuracy keeps growing. The learning outcomes are summarized in the table I.

By adding gradually neurons on the first layer, the classification performance increases from 0.26 to 0.34 with 100 and 350 neurons respectively on the first layer. This performance is seen to decrease by adding neurons until reaching 0.21 with 1000 neurons on the first hidden layer. Adding a second hidden layer allow the classification performance to increase from 0.32 to 0.62 for a number of neurons equal to 100 and 450 respectively. The same reasoning was made for layers three, four, five and six. It should be noticed that the classification performance is far much lower with 6 hidden layers. Our model contains five hidden layers with the number of neurons in each layer: 350-450-450-450-750, for the first, second, third, fourth and finally the fifth hidden layer respectively. This stopping criterion is explained by the fact that the accuracy of classification of activities is very small at the beginning of the learning phase. Then, as neurons and hidden layers are added, the accuracy increases until it reaches a threshold at which accuracy begins to decrease (hidden layer 6). We can explain this by the fact that, starting from this threshold, the DNN enters an over-fitting learning phase. The abusive addition of large numbers of neurons on the hidden layers gives the algorithm the ability to learn the data by heart. The DNN architecture is therefore set at this threshold, beyond which the algorithm will not be able to generalize to other data.

2) *Results*: The figure 5 provides a visualization of the data from test set after learning. Figure 5 shows the different classification decision surfaces of the five activities. We can see the different classes of activities. There are also some classification errors. This figure also shows the advantage of using a DNN algorithm. Indeed, the decision surfaces are

Actual \ Predicted	Predicted				
	0-90	90-max	max-90	90-0	0-0
0-90	78.60		8.80		12.0
90-max		83.66	2.94	13.40	
max-90	16.06	5.99	77.95		
90-0		3.30		76.90	19.80
0-0				20.18	79.82

TABLE II: Confusion matrix of activities detected by the DNN model in %.

nonlinear, which reduced the impact of errors induced by a possible linear classification (for example the use of a linear classifier such as SVM).

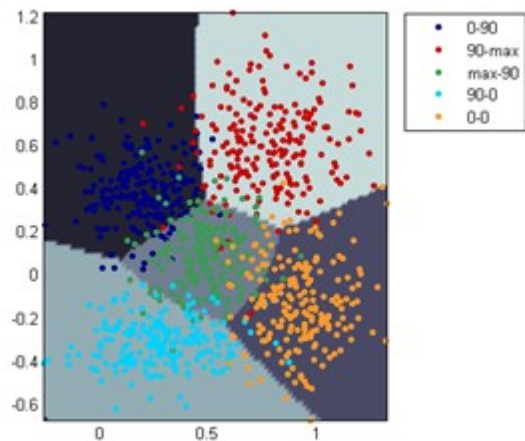


Fig. 5: Visualization of the five activity classes with the corresponding decision surfaces.

In order to understand this classification more thoroughly, we established a confusion matrix. The confusion matrix allow to determine if some activities are confused with other with a certain percentage. The results are summarized in the table II.

The 0-90 activity is confused to max-90 and 0-0 activities at respectively 8.8% and 12.6%. 90-max is confused with max-90 and 90-0 activities at 2.94% and 13.4%. max-90 is confused with 0-90 and 90-max at 16.06% and 5.99%. The 90-0 activity is confused with 90-max and 0-0 activity at 3.3% and 19.8%. Finally, 0-0 activity is confused with the 90-0 activity at 20.18%. This matrix also includes the results of the learning for each activity (78.6% for 0-90, 83.66% for 90-max, 77.95% for max-90, 76.9% for 90-0, and 79.82% for 0-0).

D. Comparative study with other methods.

To prove the effectiveness of our approach, a comparative study has been carried out using other types of algorithms: C45, Nave Bayes Classifier and Decision Trees algorithms. In order to guarantee a better learning method for these three algorithms, we have varied the size of the learning and test

	SVM	NB	DT	DNN
0-90	75.55%	70.62%	75.87%	78.6%
90-max	80.1%	70.11%	80.96%	83.66%
max-90	70.7%	68.95%	73.9%	77.95%
90-0	74.51%	66.84%	75.75%	76.9%
0-0	74.85%	65.17%	75.95%	79.82%

TABLE III: Comparison of classification details of the algorithms: DNN, SVM, DT and NB.

set. The percentage of learning and test data was varied from 50:50 (learning set: test set) to 90:10. We have chosen the best configuration to achieve the best classification results. The results are given in the following table III:

The classification accuracy of the four algorithms is between 65% and 83%. It is noted that the classification of these three algorithms is relatively good. Indeed, SVM has an average accuracy of 75.14% and 76.34% for NB algorithm. The classification process with DT algorithm is better than the SVM algorithm one. We can explain this, among other things, by the fact that DT does not undergo the problems of overfitting. Our model gives better classification results between 76.9% and 83.66%, our criterion of choice of the architecture of the model avoided an over-fitting in contrast to the two other algorithms.

V. CONCLUSION AND FUTURE WORKS

This paper presents a new approach for the assessment of elbow flexion using smart textile sensor and machine learning. This work is based on a sensor using the double bridge structure which allows better elasticity. A Deep Neural Network have been developed and optimized to remove noise and hysteresis constraints due to the constitution of the sensor. The precision of the classification varies according to the activity from 76.9% to 83.66%. The comparative study shows that the use of a DNN provides the best results in terms of classification performances.

As perspectives, studies will be carried out in order to optimize the sensor in terms of structure and composition. The placement of the sensor on the elbow joint as well as the placement of the measure points on the sensor needs to be investigated. Furthermore, a study should highlights the impact of more measure points on the angle recognition reliability. Finally, the creation of a dynamic real-time model for angle recognition will also be considered in the future.

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