k-Nearest-Neighbour based Numerical Hand Posture Recognition using a Smart Textile Glove

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***Abstract*—In this article, the authors present an interdisciplinary project that illustrates the potential and challenges in dealing with electronic textiles as sensing devices. An interactive system consisting of a knitted sensor glove and electronic circuit and a numeric hand posture recognition algorithm based on k-nearest-neighbour (kNN) is introduced. The design of the sensor glove itself is described, considering two sensitive fiber materials – piezoresistive and piezoelectric fibers – and the construction using an industrial knitting machine as well as the electronic setup is sketched out. Based on the characteristics of the textile sensors, a kNN technique based on a condensed dataset has been chosen to recognize hand postures indicating numbers from one to five from the sensor data. The authors describe two types of data condensation techniques (Reduced Nearest Neighbours and Fast Condensed Nearest Neighbours) in order to improve the data quality used by kNN, which are compared in terms of run time, condensation rate and recognition accuracy. Finally, the article gives an outlook on potential application scenarios for sensor gloves in pervasive computing.**

***Keywords*–smart textile controllers, kNN, piezoresistive and piezoelectric fibers**

I. INTRODUCTION

Artificial Intelligence (AI) research into pervasive computing deals with intelligent systems that are usually highly distributed in space with a multitude of possible input and output modalities. In addition to static distributed sensors, mobile and wearable sensors have recently become increasingly important to gather more accurate and different information on the state and performance of the user [1], e.g., to track posture, movements, or even physical and emotional states. Due to the advances in textile technology and materials research, textile sensors have emerged as a new alternative to established electronic components in wearable applications. As Roggen et al. [2] point out, textile sensors are particularly useful in wearable applications for their close proximity to the skin, potential multimodality, convenience and wearing comfort, long-term use, and user acceptance.

However, textile sensors also pose a challenge on the computing part, as they tend to be much less predictable than conventional electronic components. In fact, textile sensing materials often produce a significant amount of noise; they are subject to a lot of mechanical stress and tend to wear out over time; their performance can be dependent on environmental influences such as temperature and humidity; and their physical structure is much more difficult to model and predict before the actual production, compared to standard sensors. The use of textile sensors in a pervasive computing system therefore relies on the use of an appropriate recognition algorithm that is able to process the sensor data in a meaningful way.

In this paper, we present an interactive system that uses a textile sensing device - that is, a glove with sensors on each finger - as a wearable controller in a pervasive computing context. Through the design of a complete e-textile system, we also would like to comprehend fundamental benchmarks for a sustainable and reusable textile sensing device. Gloves are a popular and well-explored form of a wearable textile that can be used for posture and gesture recognition to interact with computational systems [3]. Data gloves have been used for sign language recognition, robot control, graphic editor control, virtual environments, number recognition, television control, 3D modelling [4]. Our goal was to provide an integrated, low-level, low-cost alternative to more accurate and sophisticated sensor gloves. Unlike most commercial systems, this system uses sensors from textile materials that are fully integrated with the surrounding structure, and therefore both lightweight and comfortable as well as cheap and easy to produce. As such, they provide a robust and mobile solution which is less sensitive to distance and lighting conditions than camera-based recognition systems, adaptable, and less complicated than commercial system with a higher sensor density and accuracy. We also explain the adaptation of existing gesture recognition algorithms for the use with the new textile sensors. We conclude with a test case to evaluate the combination of textile hardware, wearable setup and a recognition algorithm.

In section II-A, we give a brief overview of the hardware components of the interactive system we used, from hardware (sensor glove) to algorithm. We then introduce an example application for numeric hand posture recognition, for which we deployed a k-nearest-neighbour (kNN) approach, in section II-B. The experiments to compare the two kNN models based on both simulation and sensory data are described in section III together with a performance demonstration of the algorithm with a NAO robot. In Section IV, we summarize the perspective of smart textile technology used for activity recognition. We also conclude with an assessment of the challenges of applying e-textile sensors in our sensor glove application.

 ISBN: 978-1-61208-421-3

II. The Glove Control System

A. Hardware Setup

Data gloves are a popular application for wearable sensors, as they provide wearer comfort while enabling the monitoring of hand movements and postures. Existing projects have used a broad range of sensor technologies to detect finger bending, such as commercial bending sensors [5], [6], [7], optical fibers [8], [9], or printed polymer sensors [10]. The textile, in these cases, merely serves as a carrier substrate for the sensor components. In contrast, our work demonstrates bend sensitive gloves where textile fibres with sensor properties were directly integrated in the textile during the knitting process (Figure 1), resulting in a comfortable and lightweight construction. Unlike existing systems, these gloves are fabricated as one piece, with the sensors being part of the knitted structure. This approach is more similar to [11], where the sensor yarn is integrated into a hand-crocheted glove. Being fully automated, the production process and the appearance of the glove corresponds to a normal knitted glove, resulting in a lightweight and cheap wearable that could be produced on a large scale. For our glove, we considered two e-textile sensor materials, piezoresistive and piezoelectric fibers.

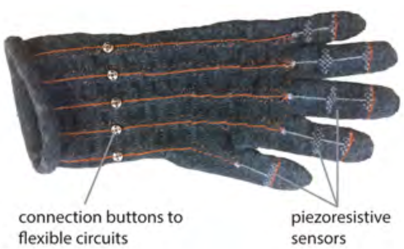

Figure 1. The e-textile glove used in our work. The light grey fibres are piezoresistive fibres. The buttons are sewn on the textiles to connect to the flexible circuit board.

1) Piezo-resistive material: Piezo-resistive materials change their resistance when deformed, i.e., pressed or stretched. While this is essentially true for all conductive materials, the material's selection for a certain application will also depend on the material's mechanical properties and its suitability for the relevant manufacturing process. Textile piezo-resistive sensors may be constituted by, e.g., silicon-based coatings filled with carbon particles [12], carbon-coated rubbery fibres [13] or conductive fibers arranged in a stretchable and elastic textile structure [14]. In our project, we use a piezo-resistive thread (Bekaert Bekinox©50/2 [15]) that is a blend of 20% short steel fibers and 80% polyester yarn with an average conductivity of $50\Omega/\text{cm}$ under strain that has been used in a similar project to produce bend sensors on a glove [11]. When in a relaxed state, only a few steel fibers make contact within the thread, resulting in a high resistance. When the thread is stretched, the steel fibers are forced closer to each other, which increases the conductivity of the material. When used as sensors, the resistance of a piezoresistive fiber is continuously measured and will be proportional to the amount of pressure or strain.

This piezoresistive thread is readily available, relatively cheap, easy to work with, making it simple to use as a variable resistor in a simple voltage divider circuit, where the voltage drop over it is proportional to its resistance. The material is not insulated and surface contact is sufficient for electrical connections. The piezoresistive effect, however, depends highly on the production conditions and composition of the sensors in a particular object: It can be influenced by the yarn tension on the knitting machine, by the density of the knitted structure, the stretchability and elasticity of the surrounding material, as well as the fit of the wearable it is part of. Also, the resistance of the material is considerably high, adding up to a resistance of up to $1\text{M}\Omega$ for a single sensor in relaxed state.

2) Piezo-electric fibers: Piezoelectric materials generate an electric voltage when deformed. This property is present in different types of materials, e.g., minerals, ceramics and polymers, and is due to a persistent polarisation in the molecular structure, which causes a change in the charge density in response to deformation. This can be measured as a transient voltage across the material's boundaries. The continuous production of the piezoelectric polymer fibers used in this work was recently presented [16]. This fibre (produced and kindly supplied by Swerea IVF, Mölndal, Sweden) can be readily processed in standard textile production methods, e.g., knitting, weaving, embroidery, and is highly sensitive to strain. For example, a textile band woven from this fibre and fastened around the chest of a person, has been shown to generate clear output signals in response to the wearer's heartbeat [17].
An advantage of piezoelectric materials is that, as opposed to the piezo-resistive ones, they generate their own voltage. In practice though, especially in polymers, the generated current is extremely small and the piezoelectric fiber must be connected to an operational amplifier working as a high impedance buffer, for the output signals to be of a useful amplitude. Thus, in comparison to the piezoresistive fiber, the electronic assembly for the piezoelectric material is more complex and requires more components.

3) Robot and its software interface: The humanoid used in our work is a commercialised robot from Aldebaran Robotics, called NAO [18]. The NAO robot has 25 degrees of freedom and multiple useful sensors (e.g., ultrasound, gyro and motor sensors). It can also perform a lot of sophisticated functions, such as dancing, walking and speaking. The software embedded in the robot is called Naoqi which works as a mid-ware to synchronise all the modules running on the NAO. In our work, the hand posture recognition module and the entertainment module are being synchronised for communicating with each other based on hand postures.

B. Data Processing

The piezoresistive sensors in the glove show a complex response to bending of one or several fingers at a time that does not correspond with a straightforward proportional increase in conductivity. This behaviour is somewhat typical for wearables. Most applications of wearable devices involve a sophisticated process of translating sensory data into context specific meanings based on a variety of computational models [2]. In order to interpret data from wearable sensors, many different pattern recognition and machine learning techniques can be used, such as neural networks [19], fuzzy logic models [20], dynamic time warping [21] and knowledge based models [22]. Generally speaking, these techniques are usually employed in an activity recognition chain which includes sequential functions of data preprocessing/segmentation, feature extraction, classification, classifier fusion, decision filtering and high-level reasoning[2]. The activity recognition chain is a salient part of the whole e-textile system consisting of a three-level design: sensor hardware, signal processing/activity analysis and high-level interaction[2]. The sensor hardware design refers to the process of sensor design and characteristics test. After a proper sensor test and signal preprocessing (which guarantees that the sensor is appropriately designed and signals are not noisy), acquired data can then be used in an activity recognition chain (ARC). In the end of an ARC, a high level interactive model (if required) might be designed for more sophisticated applications (e.g., emotion recognition, cognitive processes).

C. kNN: an algorithm for hand posture recognition

Generally speaking, there are three categories of training/learning algorithms broadly used for recognizing different hand postures with high accuracy: neural networks (NN), hidden markov models (HMM) and instance-based learning models (kNN) [3]. However, there is no guarantee that NN or HMM can converge if structure configurations of NN or HMM are inappropriately set (e.g., number of layers for NN, number of hidden states for HMM) [3]. kNN can avoid no-convergence risk as there is always a classification decision based on calculation of k nearest neighbours. We therefore choose an instance based model (kNN) because of its simplicity for implementation. Also, as an unsupervised learning technique [23], kNN is data driven, which means it has the ability of continuous training with more data. This provides an easy approach to calibrating for new users by involving their data in a continuous training process.

1) kNN algorithms: k nearest neighbours is an algorithm that classifies a new dataset x based on a training data D. x can be a dataset with m dimensions and D is a labeled database (all the datasets have been correctly labeled with classes) containing n datasets. A normal kNN should include two general steps for classifying an input dataset [24]: *a) calculate the k nearest datasets within D for the input dataset x. b) return the class that represents the maximum of the k datasets.* The nearest neighbours can be determined by the calculation based on distinct distance metrics, such as euclidean distance, minkowski distance and mahalanobis distance [24]. In our work, we use the simplest euclidean distance.

Since the distance calculation dependent on training database D directly determines the class of input dataset x, the quality of the database becomes a salient factor for kNN based classifiers. There are two factors that might potentially affect the quality of the database: a) training data size (n) and b) dimensions or attributes of data (m). Obviously, if the training data size is too large, it will deteriorate the speed of distance calculation in real time, causing the failure of algorithm implementation. In order to avoid this, a data condensation technique is needed to remove the redundancy in the training data, which then leaves the minimum number of data for sketching the probabilistic distribution of the original data [25]. On the other hand, kNN still suffers the curse of dimensionalities [26]. A dataset with too many dimensions or attributes can cause the failure of kNN classification. Solutions for this problem are using dimension reduction techniques, e.g., principal component analysis [23] and backward elimination [26]. Meanwhile, in order to have usable training data, some preprocessing techniques are necessary for standardizing the data, e.g., signal filtering (remove noise in the data), signal segmentation and normalization [3].

2) Data preprocessing: In our work, data preprocessing only involves filtering and normalization. The aim of filtering is to maximize the signal to noise ratio so that the influence of noise can diminished. The filtering has been fulfilled in electronic circuits by using standard low-pass resistor capacitor (RC) filters. Normalization is calculated on each dataset following $x'_D = \frac{x_D - min(x_D)}{max(x_D) - min(x_D)}$, where x_D and x'_D are a dataset before and after normalization, respectively. $min(x_D)$ is the minimum sensor value 0 and $max(x_D)$ is determined by the sensor value with users fully bending each finger. Then datasets are collected for postures corresponding to each respective number and captured variation when pivoting a user's wrist.

3) Data condensation: Since each dataset used in our work only contains five necessary numbers/dimensions from five fingers, the data dimension can be considered to be minimum so that dimension reduction algorithms are not used in our work. However, the size of the training data used in our work is 2000 for each posture which contains 1500 and 500 datasets for training and testing respectively. It is too large for real time implementation. Therefore, data condensation is necessary. The aim of data condensation is to find a subset of the original training data, which does not influence classification results [25]. There are a lot of types of data condensation algorithms. According to a complete survey of different data condensation techniques [27], CNN and FCNN outperform most of other algorithms with the good features of condensation rate and computation complexity. Therefore, we apply both algorithms on simulated gaussian data and hand posture data for comparison(for algorithm details, please refer to [28] and [29]).

III. Experiments and Results

In this section, we apply kNN algorithms on the sensor glove for numeric hand posture recognition. In order to clearly compare the two data condensation techniques used in the experiments, we first test their performance on a database containing three gaussian generated data classes. Then, we apply the two algorithms to the numeric hand posture database. Finally, a human-robot interaction demonstration is set up to show that a humanoid can be controlled by recognising numeric hand postures as "menu selection" input.

A. The glove textile and circuit construction

To knit a glove with each material, a Shima Seiki SWG091N industrial knitting machine with six yarn feeders has been used. The machine and the accompanying programming software provide templates for gloves that can be customized for specific hand measurements. The knitting process of a five-finger glove first produces the index, middle finger, ring finger and little finger separately, then proceeds with the upper hand part, adds the thumb and finishes the glove. This sequence requires that after finishing a finger, all yarns are automatically cut. The amount of yarn feeders limits the amount of yarns that can be used at the same time in one knit structure.

 ISBN: 978-1-61208-421-3

Given these constraints, the design of the sensors on the glove is limited to the length of the fingers and cannot easily be extended over the back of the hand. For the piezoelectric fiber, it would require re-connecting the fiber cores between the finger and the back of the hand; for both fiber types, it would be necessary to have more than six yarn feeders - one for each finger including the thumb, one for the basic material (wool), and one for the high-conductive copper thread (7/1 high flex copper thread from Karl Grimm [30]) that is used for the connections to each finger on the palm side of the hand.

Both sensor types are to a certain degree ambiguous in their response - they do not only react to stretching (i.e., bending of the fingers), but also to pressure (e.g., pressing the knuckles without bending the fingers). The two fiber types provide different kinds of signals: The piezoresistive fiber allows for continous readings of the amount of bending. The piezoelectric fiber produces an event-based signal depending on the force and velocity of the bending motion. For the posture recognition, we decided to work with a glove version that had piezoresistive sensors on all five fingers (Figure 1). While sensors and - to some extent - the electric connections can be very well integrated with the knitted structure of the glove, the more delicate electronic components of a wearable device usually have to be arranged on a more conventional substrate and then attached to the e-textile device through mechanical connections. In our case, all components other than the sensors and the connection to the sensor were mounted on a custom made printed flexible circuit board (C.I.F. AN10 1-sided plain flex circuit board with 35 microns copper layer), which was attached to the glove with snap buttons and closed around the wrist like a bracelet (Figure 2). This construction principle, which has been developed by [31], makes the sensing and communication circuit small and lightweight so that it can be conveniently used.

For both sensor gloves, we used an ATTiny 84 micro-controller as processor to read the sensor data from either the voltage divider or the amplifier (LMC 660 op amp) with a simple program that outputs the sensor data to a serial connection. The connection runs via a six-pin header that can be connected to a Bluetooth device or a FTDI board with a mini USB plug with the same footprint. The circuit can run on the power from the FTDI or on a LiPo coin cell battery placed in a small pouch on the flex circuit itself. For the piezoresistive glove, large capacitors (1μF) have been added parallel to the pullup resistors for filtering. 1).

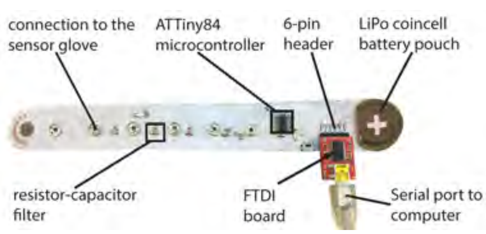

Figure 2. The flexible circuit wearable on one's wrist with component names and labels.

B. Test on simulation data

In order to visualise how the two data condensation techniques perform, we chose to test them with a simulation training database with three gaussian generated classes. Each data set contained a two dimensional coordinate in a $x - y$ space and each class contained 500 datasets. The testing database included 300 data of which each class had 100 datasets. The condensed database based on CNN and FCNN is shown in Figure 3.

From results shown in Figure 3, we clearly see that the FCNN condensed database is more aligned close to the borderlines separating every two classes except for the centroids. However, the CNN condensed database contains less data and is more distributed within the class clusters. In machine learning, finding class borderlines is very useful and important for classifiers such as a support vector machine, regression models, neural network and kNN[23]. Also it is more convenient to classify input data based on an FCNN condensed database with clear class boundaries. When verifying the trained model with the kNN rule (k = 3) based on the testing database, the accuracy rate is 98% and 93% for FCNN and CNN condensed data respectively. Clearly, in the case of simulation data, FCNN outperforms CNN in terms of accuracy. However, it takes less than 2 minutes to run CNN, compared to 10 minutes for FCNN.

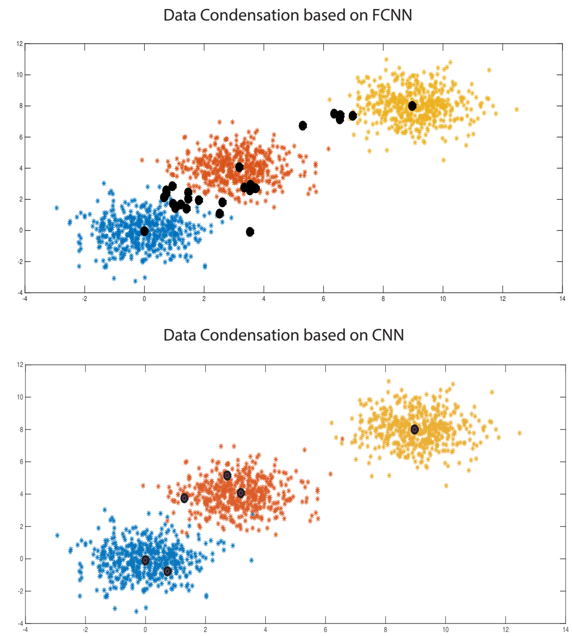

Figure 3. Upper: original database (shown in blue, red and yellow for three classes) and FCNN condensed database (black). Down: original database (shown in blue, red and yellow for three classes) and CNN condensed database (black).

C. Hand posture recognition experiments

The numeric hand postures (from 1 to 5) adopted in our experiments are shown in Figure 4. Using the sensor glove, 8000 datasets was collected from one user; each posture corresponds to 2000 datasets. For each posture, the database was split into 1500 for training and 500 for post-training test. Each data contained five dimension input from each finger respectively. Then, CNN and FCNN were used to extract condensed data out of 6000 datasets. We assume that a calibration process (retraining) needs to be done for each user since every user has different hand size. The results of the comparison between CNN and FCNN are shown in Table I.

Figure 4. Hand postures representing numbers from 1 to 5 (from left to right).

TABLE I. Comparison of CNN and FCNN

Algorithms	Training Time (seconds)	Condensed rate	Accuracy
CNN	127.543s	94.43%	75.4 %
FCNN	5 hours (approximately)	87.5%	96.3 %

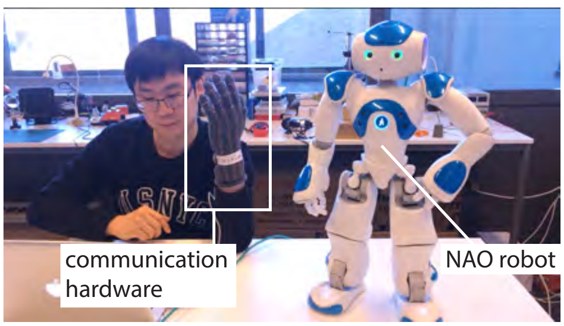

Figure 5. The sensor glove used in a human robot interaction demonstration.

From the results in Table I, we can draw some conclusions about the comparison of the two condensation techniques: a) in terms of condensation rate, CNN tends to remove more data than FCNN while FCNN can classify with much higher accuracy. There might be a trade off between condensation rate and classification accuracy. b) The training time of CNN is rather shorter than FCNN as FCNN is an incremental algorithm which involves a thorough database search for every incremental step. This result is similar to the results obtained by Amal et al [27] pertaining to the advantages and disadvantages of different data condensation techniques. With condensed datasets, kNN algorithms can run very fast. The response time for a new posture changed from a previous one is on average smaller than 0.01s compared to 1.2s for non-condensed datasets.

D. A robotics demonstration

Finally, the use of a self-designed sensor glove as an external controller to interact with a humanoid has been demonstrated. This human robot interaction relied on a previously trained classifier in real time, requiring the classifier to be both accurate and fast-responding. Three games were designed for the user to try on the NAO robot (Figure 5). The user could use hand gestures to communicate with the robot both to select which game to play, and to actually play it. For example, in the game named "number reaction", the user needed to react with hand postures to a number said by the NAO robot. This fully demonstrates the function of kNN model working with the sensor glove. As a result, the well-trained classifier could quickly determine hand postures in real time from data streams (Please refer to the video [32]).

IV. CONCLUSION

A. Challenges for our e-textile glove system

In this article, we demonstrated a smart textile glove used as a controller for an application in a robotics control context. Presumably, the smart textile glove can also be applied to control other pervasive devices which are communicable and controllable to our systems. However, there are still some challenges in our system, due to the variability in the characteristics of textile sensors:

- Sensitivity – In this particular e-textile system, the upper finger knuckles were not covered by the sensors, which reduces the sensitivity of the sensors for detecting finger bending. The extent and placement of the sensors can be improved by elongating the sensor to cover all finger knuckles and to use a looser fit for the glove, e.g., by adding elasthane to the non-conductive basis material.
- Hysteresis– Textile materials typically exhibit stress relaxation and creep, causing the sensitivity to degrade after a certain period of constant use. This fact limits the textile materials useful in sensor applications to those with high elasticity and good ageing properties, but also inevitably introduces a factor of time dependence in all measurements. One solution might be setting up a periodic test for the sensor glove to measure and record the variation of the sensors, and establishing a model to statistically describe the variation in order to compensate/cancel effects of deterioration.
- Offset – A textile sensor will typically have a pre-strain, depending among other things on the size of the wearer. Integrating data from a large number of users is of great importance to establish a general calibration system making the sensor glove easily reusable. In our system, we use a retraining strategy to solve this problem. Obviously, retraining for every user will increase calibration time. A solution to this problem might be to statistically model the probabilistic variation of data from different users and establish a general calibration system which has the ability to integrate new data to reduce calibration time.

B. Future work

In future work, the whole sensor glove system needs to be improved from three different perspectives: a) Improvement on hardware design. Considering the constraints of the knitting machine, different knitting patterns and techniques must be tried to provide a more meaningful sensor allocation on the back of the hand. This might be achieved by combining piezoelectric fibers (to detect the bending motion) with piezoresistive fibers (to detect the posture). b) Improvement on the activity recognition chain. Calibrating the "ground truth" of the sensor glove is necessary to establish an accurate model for different hand gestures. This needs a detailed model of hand kinematics by clarifying the variation of sensor

 ISBN: 978-1-61208-421-3

sensitivity and users' different hand sizes. The final aim of ground truth modelling is to accurately map one user's hand motion into a 3-dimensional Cartesian space. c) Improvement on applications. We assume that a simple numeric hand posture recognition system can be extensively developed to a sign language interpretation system. This is useful for helping speechless people to communicate with an intelligent machine. This application upgrade involves not only improvement on hardware by increasing the sensor functionality, but also by improving techniques for interpreting dynamic hand gestures in a sequence instead of only recognizing static hand postures.

ACKNOWLEDGEMENTS

The financial support of Västra Götalandsregionen (VGR), grant number RUN 612-0197-13, is gratefully acknowledged.

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