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Gait Modeling for Human Identification

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Abstract— **Human gait is a kind of dynamic biometrical feature which is complex and difficult to imitate, it is unique and more secure than static features such as password, fingerprint and facial feature. Analyzing people walking patterns, their "step-prints", can lead to the recognition of personal identity. In this paper, we propose to design, build, calibrate, analyze, and use wearable intelligent shoes; then focus on classifying the wearers into authorized ones and unauthorized ones by modeling their individual gait performance. Firstly the intelligent shoes for collecting and modeling human gait to measure an unprecedented number of parameters relevant to gait are presented. Then we introduce Cascade Neural Networks with Node-Decoupled Extended Kalman Filtering (CNN-NDEKF) [1] to apply for modeling and classifier generation. Finally, the experimental results of learning algorithms and comparison are described and verify that the proposed method is valid and useful for human identification.**

I. Introduction

A. Motivation

In recent years, researchers have begun to focus on wearable computers and sensor interfaces. One major benefit provided by wearable intelligent devices is that they are in close proximity to the users so that human data such as motion and physiological information can be obtained and analyzed anywhere at anytime. One niche for wearable devices useful to human has, however, remained relatively unexplored - namely, the design and implementation of sensor and computer-equipped intelligent shoes. The ongoing miniaturization revolution in electronics, sensor and battery technologies, driven largely by the cell phone and hand-held device markets, has made possible an intelligent-shoe implementation. Along with these hardware advances, progresses in human data modeling and machine learning algorithms have also made possible the analysis and interpretation of complex, multi-channel sensor data. Therefore, we propose to design, build, calibrate, analyze, and use wearable intelligent shoes to measure an unprecedented number of parameters relevant to gait.

Each person has a unique walking style. We sometimes can even recognize our friends by only looking at their walking style from afar, or by listening to the sound patterns they make when they walk. The unique identity of a person can be identified by analyzing the fingerprints, voiceprints, and facial features. Similarly, analyzing the way the people walk - their "step-prints", can also lead to the recognition of personal identity. Some work for human gait focused on foot parameter detection, such as temperature, humidity, heel off time, gait velocity, and so on. There is little work to analyze the foot signal. As such, we propose to identify individuals by modeling their gait patterns. Also, embedded force, inertial and motion sensors in the intelligent shoe can offer important clues about the current activity of a user.

In modeling human gait, as with other poorly understood phenomena, we must rely on modeling by observation, or learning, rather than theoretical or physical derivation. An individual's gait is characterized by unique, complex, and unknown properties; as such, we require a learning paradigm that can cope with many difficult challenges, first of all, little if anything is known a priori about the a), structure, b), order, c), granularity, or d), delay. Second, human gait is dynamic, stochastic, and nonlinear in nature. Humans are not machines, and their gait are prone to gradual changes over time. In addition, human gait data can vary smoothly as well as discontinuously with sensory detection. In order to address these challenges, the CNN-NDEKF mentioned above can satisfy the requirement from learning human gait data.

B. Related Work

Some initial intelligent shoe systems have been prototyped. In particular, Skelly [2] has presented a rule-based gait event detector with fuzzy logic and concluded that two force sensitive resistors (FSRs) per insole are sufficient for gait event detection during walking. The robustness however to nonwalking activities (shifting the weight from one leg to the other) is questionable. Williamson [3] has reported excellent detection reliability by using three accelerometers attached to the shank and a machine-learning algorithm to detect in real time the transitions between five gait phases during walking, but no results have been presented for a use of this system with an FES system. The Salisbury Group (U.K.) [4] has administered to several hundreds patients the Odstock dropped foot stimulator (ODFS). The foot switch indicates the heel-off and the heel-strike phases. The subjects learn to keep the foot switch pressed when they stop walking in order to avoid false stimulation triggers.

Moreover, various gait system is built with more functions and more signals for motion research. Morley [5] has have developed an electronic system for a shoe that monitors temperature, pressure and humidity; however, only a hardware design is presented and there is no discussion of how the collected data is analyzed. Paradiso [6] has developed a wearable computer system for digital music that consists

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of a pair of instrumented sneakers for interactive dance. In this work, researchers have created a few musical mappings with the shoes for computer-augmented dance. Also, Morris [7] has developed a compact, wireless, and wearable sensor package that is designed to provide continuous and realtime monitoring of gait for clinical applications. Finally, Pappas [8] has proposed to analyze human gait patterns by using sensors attached to shoes; their system can distinguish walking from loading, unloading or sliding of the foot.

To date, many researchers have analyzed foot motion through a set of heuristic rules. This approach, however, is only effective for simple motion patterns. Moreover, action recognition is typically based only around that of simple motions of single individuals. We seek to expand both the flexibility and adaptability of shoe-based interfaces through our proposed intelligent-shoe system - flexibility to deal with a larger set of motion types and monitoring tasks, adaptability across many individuals, not just single individual. Also, our system will be the first to incorporate sensors in shoes for real-time human identification.

C. Paper Overview

In this paper, wearable intelligent shoes is designed, built, calibrated, analyzed, and used to measure an unprecedented number of parameters relevant to gait. The system is designed to collect data unobtrusively, and in any walking environment, over long period of time. It is built to be worn on the shoes, without interfering with gait. The sensors are calibrated, and the calibrated data are analyzed for information about the gait of the user. Based on real-time gait signal analysis, we can monitor human gait and identify human by his gait. We treat gait as a human identification mark.

The sections of this paper are built up as follows. In section II, the intelligent shoes design will be introduced as an information acquisition platform to sense the foot motion. The system is small, portable and wearable. The platform is mainly composed of four parts including a sensing module, a computing module, a wireless communication module, and a data visualization module.

We introduce Cascade Neural Networks with Node-Decoupled Extended Kalman Filtering (CNN-NDEKF) to model human gait performance. The mathematic description of CNN-NDEKF will be discussed in Section III.

Furthermore, Section IV is devoted to present human identification with CNN-NDEKF models. The experimental result on human identification is also showed in this section.

Finally, the proposed method has produced satisfactory results on human identification during test, and conclusions are presented in Section VI.

II. HARDWARE DESIGN

The proposed shoe-based information gathering platform consists of four subsystems. Fig. 1 shows the architecture of our proposed platform.

Subsystem 1 is for sensing the parameters inside the shoe. A variety of sensors are installed inside the package, including force sensors, bend sensors, accelerometers, etc. For the ease of use, we limit the size of each device as small as possible. Existing MEMS technology makes it possible to integrate all the sensors and circuits inside a small module.

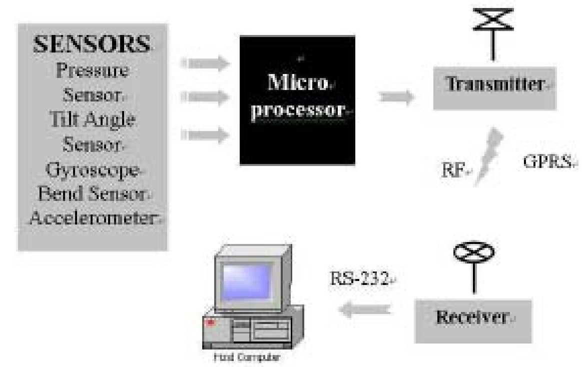

Fig. 1. Outline of the hardware design and sensor

Subsystem 2 is for gathering data from the sensors inside the shoe and sending the processed data to the wireless module. The processing power of micro-processor is limited. It can only perform some simple calculations such as counting and averaging.

Subsystem 3 is for wireless communication. This communication system is composed of an emitter and a receiver. The receiver is for collecting the data from the circuits described in subsystem 2 while the emitter is for sending the data to the host computer for further analysis.

Subsystem 4 is for visualization of the data. The received data is stored and displayed in real-time on the screen of the host computer as a visual interface. This visual interface can be used for further applications.

The outlook of the Intelligent Shoe is shown in Fig. 2.

Fig. 2. Outlook of Intelligent Shoes

A. Sensing the parameters inside the shoe

To detect the important parameters and features of gait, a variety of sensors are installed in the shoes, including force sensors, bend sensors, switch sensors, accelerometers, gyro sensors and ultrasonic sensors. Existing MEMS technology

Fig. 3. A flexible instrumented insole

makes it possible to integrate all the sensors and circuits inside a small module.

Force sensitive resistors (FSRs) and switch sensors are selected to detect the gait timing and pressure parameters. The force sensors operate with a voltage source and a fixed resistor to produce a voltage that changes with the applied forces. Two FSR402 sensors are put under the first and fifth metatarsal head, and other two FSR400 sensors are put medially and laterally underneath the heel pad, where support the most of force through walking. We put two switch sensors under the bigtoe and the heel, to provide additional information about gait timing. Though four FSRs can't detect force distribution of whole foot, we can get the main force feature and gait timing parameters for identification training.

One bend sensor is selected for gait flexion detection. The bend sensor is put in the insole under bigtoe and heel. The resistance of bend sensor changes as it is bent, which can provide information about flexion between the toe and the heel. The output of the bend sensor also contains rich information about human motion, especially loading and uploading of feet.

We select three single-axis gyroscope sensors and a three-axis accelerometer to detect motion orientation of the foot. Three single-axis MEMS gyroscope sensors (ENJ-03J Murata) are mounted. As a miniature vibrating-read gyro, it uses piezoelectiric material to sustain vibration, while taking advantage of Coriolis forces to measure angular rate. Each gyro sensor can test one angular rate in one direction; thus we can measure yaw, roll and pitch of shoe motion. Also, a three-axis MEMS accelerometer (MMA7260Q Freescale Semiconductor) is mounted, which can detect the acceleration motion of shoe in three dimensions. The gyroscope sensors and acclerometer can detect three-dimension rotation parameters and three-dimension acceleration parameters, which can be called Inertial Measurement Unit(IMU).

On the other hand, one ultrasonic sensor is added to measure the height between the shoe and the ground. All sensors installation can be seen in Fig. 2 and Fig. 3.

B. Gathering information from the sensors

This subsystem is mainly composed of a processor circuit board. The original analog signal generated by the sensors is transmitted directly to the ADC channels of the micro-processor(ATMega 8535). After A/D transform, the digital signal is passed to wireless communication module through the TXD port for transmission to PC for data analysis and visualization. A micro battery cell will also be added to serve as power supply. The circuit board is small and it can be easily put into the heel of the shoe so that users will notice little the difference between normal shoes and the intelligent shoes.

C. Wireless communication

This subsystem is for transferring the data from the shoe to the host computer. Many foot-based gait analysis system do not use wireless system as it will introduce many transmission errors that make the analysis result unstable. In our system, the size of the data is relatively small and it is possible to use a wireless system. We select GW100b wireless communication module, which has 192000bps transmission speed and low power consumption less than 10mW. With embedded micro-processor, GW100b can realize Forward Error Correction (FEC), which observably reduces transmission error and improves wireless communication reliability. At the same time, with the same power consumption and error rate requirement, GW100b can transmit data for further distance with the help of FEC than other wireless communication modules without FEC function. The wireless communication process flow is shown in Fig. 4.

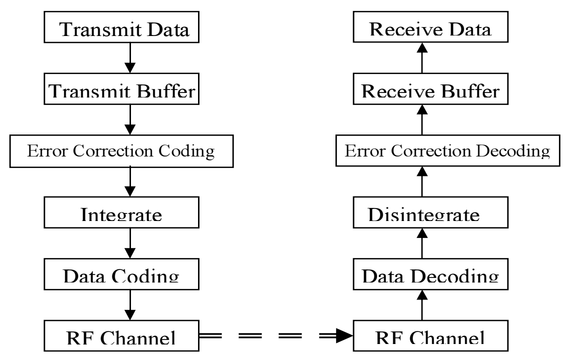

Fig. 4. Wireless Communication Process Flow

D. Data visualization

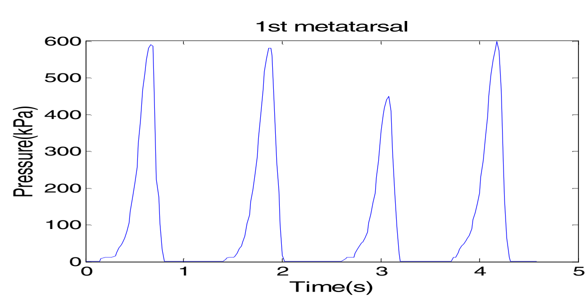

Fig. 5. Time domain pressure signal of 1st metatarsal

As this platform is designed for general applications, we display all parameters measured from the shoe. The host

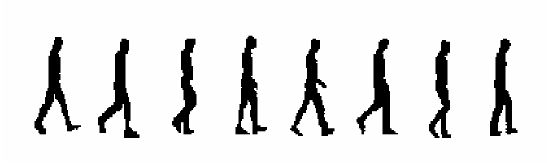

Fig. 6. A walking person by animation

computer gets the data from the wireless receiver via RS232. Different functions for visualizing the data from different sensors are developed and compacted. As an example, Fig. 5) describes the realtime pressure signal of 1st Metatarsal. We can also visualize a walking person by animation (in Fig. 6), which is mapped from different motion status of the person. All of the above provide a friendly interface to display the data of the sensors obtained from the shoe.

III. Cascade Neural Network with Node-Decoupled Extended Kalman Filtering for Gait Modeling

Our goal is to separate the wearers into two classes: authorized wearer and others, according to a group of features. We address this classification problem as a binary pattern recognition with CNN-NDEKF.

In recent years, neural networks have shown great promise in identifying complex non-linear mappings from observed data, and have found many applications in non-linear system. Despite significant progress in the application of neural networks to many real-world problems, however, the vast majority of neural network research still relies on fixed-architecture networks trained through backpropagation or some other slightly enhanced gradient descent algorithm. There are two main problems with this prevailing approach. First, the "appropriate" network architecture varies from application to application; yet, it is difficult to guess this architecture, the number of hidden units and number of layers - a priori for a specific application without some trial and error. Even within the same application, functional complexity requirements can vary widely, as is the case, for example, in modeling human tracking strategies from different individuals [1]. Second, the backpropagation and other gradient descent techniques tend to converge rather slowly, often exhibit oscillatory behavior, and frequently convergence to poor local minima.

Therefore, Nechyba and Xu[9]developed a new neural network learning architecture to counter these problems mentioned above. This neural network is well known flexible Cascade Neural-Network with Node-Decoupled Extended Kalman Filtering (CNN-NDEKF). Below, we briefly summarize the CNN-NDEKF training algorithm and why we selected this learning algorithm to model human gait and capturing walking feature. First, no a priori model structure is assumed; the neural-network automatically adds hidden units to an initially minimal network as the training requires. Fig. 7 illustrates how a two point, single-output network grows as two hidden units are added. Thus, a cascade network with inputs, hidden units and outputs, has connection where,

$$\mathrm{n}_w = n_{in} n_0 + n_h(n_{in} + n_0) + (n_h - 1)\frac{n_h}{2} \quad (1)$$

Second, hidden unit activation function is not constrained to be a particular type. Rather, for each new hidden unit, the incrementally learning algorithm can select that functional form, which maximally reduces the residual error over the training data. Typical alternatives to the standard sigmoidal function are sine, cosine, and the Gaussian function.

Finally, it has been shown that NDEKF, a quadratically convergent alternative to slower gradient descent training algorithms, such as backpropagation or quickprop, fits well within the cascade learning framework and converges to good local minima with less computation. NDEKF is a natural formulation for cascade learning for we only train the input-side weights of one hidden neuron and the output units at any one time; we can partition the m weights by unit into groups-one group for the current hidden unit, groups for the output units. In fact, by iteratively training one hidden unit at a time and then freezing that unit's weights, we minimize the potentially detrimental effect of the node-decoupling.

Denote ω_k^i as the input-side weight vector of lengths m_i at iteration *k*, for unit $i \in 0, 1, \ldots, n_0$, where $i = 0$ corresponds to the current hidden unit being trained, and $i \in 0, 1, \ldots, n_0$ corresponds to the *i*th output unit.

The NDEKF weight-update recursion is given by

$$\omega_{k+1}^i = \omega_k^i + (\psi_k^i)^T (A_k \xi_k) \phi_k^i \quad (2)$$

where ξ_k is the n_0-dimensional error vector for the current training pattern, ψ_k^i is the n_0-dimensional error vector for the partial derivatives of the network's output unit signals with respect to the *i*th unit's net input, and

$$\phi_k^i = P_k^i \zeta_k^i \quad (3)$$

$$A_k = (I + \sum_{i=0}^{n_0} [(\psi_k^i)^T \phi_k^i][\phi_k^i (\phi_k^i)^T])^{-1} \quad (4)$$

$$P_{k+1}^i = P_k^i - \phi_k^i)^T (A_k \phi_k^i) \phi_k^i (\phi_k^i)^T + \eta I \quad (5)$$

where $\psi_k^i)^T$ is the m_i-dimensional input vector for the *i*th unit, P_{k+1}^i is the $m_i \times m_i$ approximate conditional error covariance matrix for the *i*th unit, and η is a small real number which alleviates singularity problem for P_{k+1}^i.

The flexible functional form which cascade learning allows, is ideal for modeling human gait and capturing walking feature. By making as few aprior assumptions as possible in modeling gait, we improve the likelihood that the learning algorithm will converge to a good model of the walking data.

The skill that we are considering is modeling human gait to realize human identification. Here, we consider the human gait as the measurable stochastic process and the knowledge behind it as the underlying stochastic process. A CNN-NDEKF is employed to generate classifier for human

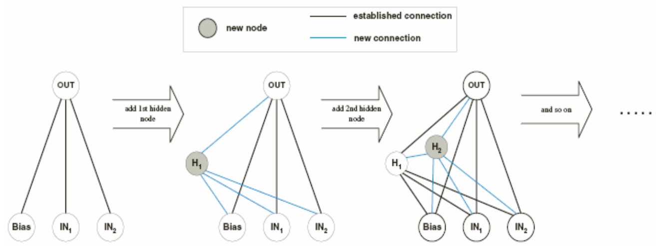

Fig. 7. The Cascade Learning Architecture

identification, and the model parameters are updated through a learning process that ensures that the model best represents the training data. Based on the trained model and the most likely performance criterion, the best data is selected from all the recorded data files. The procedures for CNN-NDEKF-based learning can be summarized as follows:

1. Initially, there are no hidden units in the network, only direct input-output connections. These weights are trained first, thereby capturing any linear relationship between the inputs and the outputs.

2. With no further significant decrease in the root mean square (RMS) error between the network outputs and the training data (eRMS), a first hidden unit is added to the network from a pool of candidate units. These candidate units are trained independently and in parallel with different random initial weights by using the quick-prop algorithm.

3. The best candidate unit will be selected and installed into the network if no more appreciable error reduction occurs, therefore, the first hidden node is produced.

4. Once the hidden unit is installed, the hidden-unit input weights are frozen, while the weights to the output unit are going to train again. This allows for such faster convergence of the weights during training than a standard multi-layer feed-forward network.

5. This process (from step2-step4) is repeated until the eRMS reduces sufficiently for the training set or the number of hidden units reach a predefined maximum number.

IV. Experimental Results

In this experiment, we try to recognize whether there is any unauthorized person wearing the shoes by analyzing the real time gait performance.

A. Database

In order to estimate the gait performance of the proposed system, we invite 9 human subjects to wear the Intelligent Shoes system, who are HUANG, CHA, LIANG, MENG, SHI, WANG, XIA, YE, and ZHONG. The gait data are collected and then classified through CNN-NDEKF into 2 group: HUANG as the authorized wearer and other 8 people as the unauthorized wearers.

The sampling rate is set at 50 Hz based on the gait motion frequency. 5784×28 data segment can be produced by HUANG as authorized wearer data, and 12663×28 data segment by other 8 wearer as unauthorized wearer data for evaluation. Applying Fast Fourier Transform data processing, we can change the data to 5784×84 and 12663×84 with three order FFT. A set of eigenvectors can be computed from training data and some of eigenvectors are selected for classification according to the value of corresponding eigenvalue.

B. FFT, PCA and ICA

We compare the data preprocessing using original data, FFT, PCA and ICA. Table I shows the test results using different data preprocessing methods. With the same training and testing sample, the retrieved vector is trained in the CNN-NDEKF and the testing results are listed in Table I. FFT is found effectively to apply to data preprocessing for Intelligent Shoes original data, and data preprocessing method based on FFT is found to give the best data classification results compared to the other two processing methods presented.

TABLE I

Test results using different preprocessing methods.

Preprocessing method	Errors of authorized	Errors of unauthorized
Original data	1500	3369
FFT	142	889
PCA	259	1582
ICA	285	1503

C. Error and Hidden Unit

Besides of previous parameters, *MaxHidden* is important to the regression result. We compare, in Fig. 8, the number of Maximum Hidden Unit and error identification rate of the learning machine with *MaxHidden* set to different value.

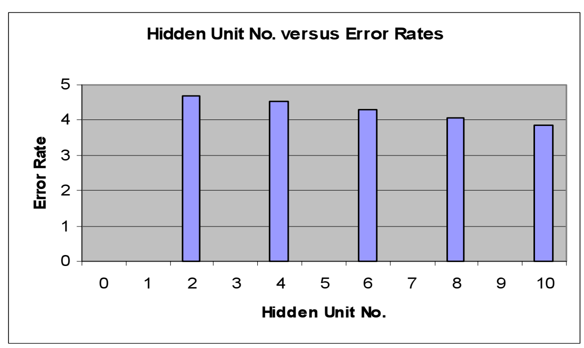

Fig. 8. Hidden Unit No. versus Error Rate

As shown in Fig. 8, when *MaxHidden* is 10, the testing accuracy is 96.133%. This result proves that our approach can get a very high accuracy in human identification with Intelligent Shoes. When *MaxHidden* increases from 2 to 10, the error rate reduces from 4.692% to 3.867%. Although larger *MaxHidden* corresponds to higher testing accuracy, as well as more iterations, to avoid the over fitting, it can not be too large. Further explanation is required for the balance between the regularization term and the training errors. Thus, a larger *MaxHidden* generate a higher accuracy and however over fitting will occur.

D. Final Testing Result

Then we utilize the aforementioned methods in real time human identification based on gait analysis with Intelligent Shoes. Corresponsively, Table. II shows the identification performance to each wearer. It can be seen that there are 4220 HUANG gait performance data applied in the evaluation process, 4081 of them are identified as authorized wearer and success rate is 96.71%. On the other hand, 21786 data collected from 8 testers are used for the test and 21126 of them are classified as unauthorized wearers successfully. The average accuracy is 96.97% and the worst classification accuracy is 89.14%. The table illustrates that there is an excellent agreement between the model and experimental results throughout identification based on gait analysis with intelligent shoes.

TABLE II

TEST RESULTS ON INDIVIDUALS.

No.	Name	Totals	Correct	Failed	Successful rate
1	HUANG	2013	1906	107	94.68%
		2207	2175	32	98.55%
2	CHA	1178	1164	4	98.81%
		1359	1345	14	98.97%
3	LIANG	1705	1663	42	97.54%
		1618	1533	85	94.75%
4	MENG	1160	1034	126	89.14%
		1329	1238	91	93.15%
5	SHI	1272	1260	12	99.06%
		1211	1201	10	99.17%
6	WANG	1450	1444	6	99.59%
		1392	1368	24	98.28%
7	XIA	1544	1474	70	95.47%
		1376	1340	36	97.38%
8	YE	1380	1356	24	98.26%
		1334	1324	10	99.25%
9	ZHONG	1261	1190	71	94.37%
		1217	1182	35	97.12%
TOTAL		26006	25207	799	96.93%

V. CONCLUSIONS

In this paper, we have built intelligent shoes for human identification under the framework of capturing and analyzing dynamic human gait. Firstly, data is collected from different sensors installed in the shoe. Secondly, the data is computed and transmitted wirelessly to the host computer. Finally, the data is visualized on the screen. The platform is scalable and programmable. By utilizing this dynamic property we focus on the research ideal of classifying the wearers into authorized ones and unauthorized ones by modeling their individual gait performance.

Realtime gait parameters will be collected from 9 wearers and then processed through Fast Fourier Transform (FFT) for data preprocessing and feature generation. Cascade Neural Networks with Node-Decoupled Extended Kalman Filtering (CNN-NDEKF) will be applied for training and classifier generation. The experimental results verify that the proposed method is valid and useful with a success human identification rate about 96.93%.

In the future, more experiments will be conducted on potential user groups to realize multi-object identification, and find out more precise system and wider applications. We will also introduce Hidden Markov Models(HMM) to achieve and compare the modules of multi-object identification. The proposed research opens up tremendous new human-computer interface possibilities, resulting in rich academic research contents and potential product lines in consumer electronics and multimedia industries.

VI. ACKNOWLEDGMENTS

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