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Online stress detection using psychophysiological signals for implicit human-robot cooperation

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SUMMARY

Robots are expected to be pervasive in the society in a not too distant future where they will work extensively as assistants of humans in various activities. With this in view, a novel affect-sensitive architecture for human-robot cooperation is presented in this paper where the robot is expected to recognize human psychological states. As a demonstration, an online heart rate variability analysis to infer the mental stress of a human engaged in a task is presented. This technique involves real-time heart rate monitoring, signal processing using both Fourier Transforrn and Wavelet Transform, and inferring the stress condition based on the level of activation of the sympathetic and parasympathetic nervous systems using fuzzy logic. Results from human subject trials are presented to validate the presented methodology. This stress detection technique is expected to be useful in the future human-robot cooperation activities, where the robot will recognize human stress and respond appropriately.

KEYWORDS: Affect recognition; Wearable computing; Heart rate variability (HRV), Interbeat Interval (IBI); Power Spectral Density (PSD); Fourier transform (FT); Wavelet Packet (WP) analysis; Fuzzy Logic; Human-robot cooperation.

1. INTRODUCTION

Robots are expected to communicate with humans in a variety of applications in the future. For robots to interact constructively and intelligently with human beings in work or play environments, it is helpful that they have the ability to detect and interpret the basic human affective responses. Consider several human-robot exploration scenarios in space, underwater, Antarctica, inside a dormant volcano and in other similar risky environments where a human can often encounter dangerous situations. The first reaction to such situations will likely to be panic, fear, anxiety or stress. A robot that is capable of sensing these internal psychological states can immediately take meaningful actions to help the person. A similar situation may arise in human-robot search and rescue operations or in fire fighting. The US military is considering introducing a large number of robots in the battlefield along with a small number of human soldiers to reduce human casualties in future warfare. A robot that can implicitly sense when a human is wounded or is in fear of losing his/her life and can come to the rescue immediately can be immensely helpful, because in such situations there may not be sufficient opportunity to call for explicit help. Helping disabled people is another major potential application. Robotic aid for rehabilitation could use affect sensing capability to provide exercise sequences that are comfortable for the person. A robot that could sense the fatigue of the worker on the shop floor with whom it works would be able to take necessary precautions to avoid accidents. The toy robotic industry could benefit from such research where a robot that could understand and respond to the emotions of a child could be very successful in engaging children.

The main goal of the present work is to investigate how to incorporate implicit communication from human to robot so that the robot can "understand" the psychological state of the human with whom it works. Implicit communication, in the context of the present work, is defined primarily as *affective communication* where the affective state and other implicit states such as frustration, stress and fatigue of the person is interpreted by the robot. It is well argued in the psychological literature that the affective state of a person is very important in relationships.[1–5] For example, understanding our affective states and behaving responsively are determining factors in our choice of friendships. It follows with respect to personal computers and personal robots, that if such a system could understand the affective state of a person with whom it works, the human-robot interaction could achieve a different dimension.

It is difficult to precisely define what "understanding" a person means. However, it can be argued that if a robot can recognize the affective and other implicit states of a person, and can infer the cause of these states as related to the task, it will achieve some degree of understanding. The need for a computer to understand human emotion is discussed in references [6–8]. Such a capability, alone or in conjunction with other capabilities that allow explicit instructions from a human, is expected to provide a new paradigm for human-computer (and human-robot) interaction that will be *intuitive*, *smoother* and *more efficient*. Figure 1 presents affect-sensitive human-robot coordination architecture.

In this work, we focus on the first part of the architecture, namely affect recognition through physiological sensing. We use physiological sensing because of two reasons. One, if we include all types of the physical activities that are available to infer affective states such as gestures, facial

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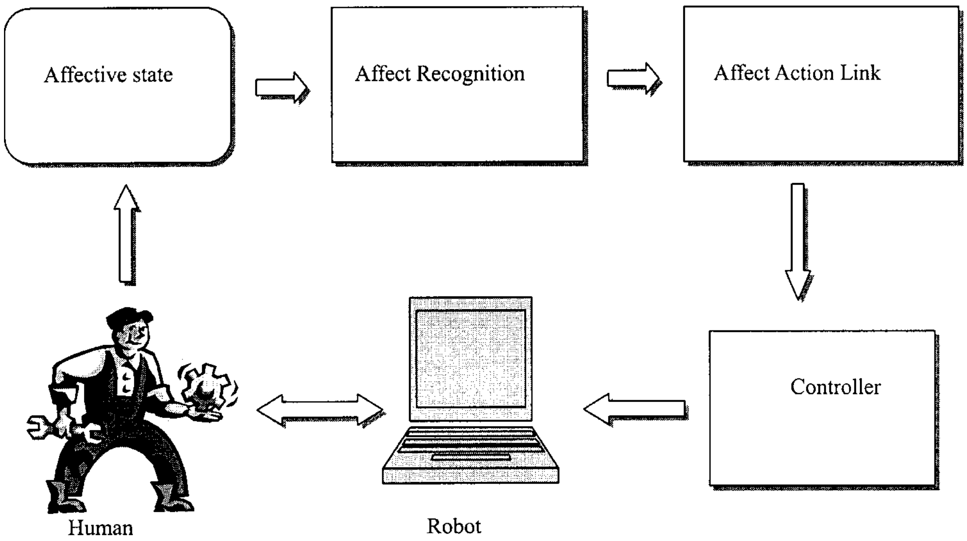

Fig. 1. Affect-sensitive human-robot coordination architecture.

expressions, intonation etc., then the problem will be immensely complex, theoretically and computationally. Two, some physical expressions are somewhat culture, gender, and age dependent. This poses difficulties in analyzing them. Physiological responses, on the other hand, are generally involuntary and less dependent on those factors. They offer an avenue for recognizing affect that may be less obvious for humans but more suitable for computers, which can quickly implement signal processing and pattern recognition tools to infer underlying affective states. With the above-mentioned applications in mind we investigate in this paper how a robot can detect stress during a human-robot cooperative activity using physiological signals. Stress is an important psychological state that, if detected in time, can be useful in many applications such as avoiding accidents in factory shop floor. The idea here is, if the robot can detect the stress fast enough, it can respond to the need of the human in real-time. There are sophisticated medical diagnostic techniques that can detect stress in a patient. All those techniques are slow, expensive, and more importantly not suitable for a person who is moving and working – a necessary condition for human-robot activity. However, recent advances in *wearable computers* and *affective computing* have ushered us in the era of small and lightweight biofeedback sensors. These sensors are unobtrusive, comfortable for the user to wear, and fast enough for real-time applications. Hence, they can process physiological signals in a non-invasive manner. Such capabilities inspire us to use physiological sensing as an initial means to recognize human affect for our proposed controller.

In this paper we propose a new method for online stress detection of humans using wavelet packets decomposition and fuzzy logic. This method is designed in such a way that it can be integrated with a robot controller so that a stress-sensitive human-robot activity becomes feasible. However, the integration of this stress detection technique with a robot controller is beyond the scope of this paper and is the subject of future work. The stress detection technique has been verified by human subject trials and the results are presented in the paper.

2. THEORY

The theoretical background of the present stress detection methodology can be divided into three parts: the physiology of stress generation, signal processing of Heart Rate Variability, and decision-making using fuzzy logic.

2.1. Physiological Aspects of Stress Detection

The human Peripheral Nervous System carries information between the body and the Central Nervous System (CNS). This information can either be input from the sensory receptors or it can be output from the CNS to an organ of the body. This output carrying system is known as the Efferent Division and is further subdivided into the Somatic and Autonomic Nervous Systems (ANS). The Somatic Nervous System is the system a person has voluntary control over. This is the system that controls the skeletal muscles for body movement and other voluntary activities. The ANS, also known as the involuntary nervous system, has control over actions in the body that one does not have conscious control over. The ANS controls smooth muscle, gland activity and cardiac muscle. It is this system of the body and its control over cardiac function that is of interest for stress detection.

The Autonomic Nervous System is further divided into two branches, each with a role in cardiac activity. The sympathetic nervous system (SNS) is the branch with dominant function in emergency situations or so-called "fight or flight" situations. The parasympathetic branch (PNS) is the relaxed activity controller. The PNS promotes body maintenance such as food digestion. Increased activity of the sympathetic branch causes an increase in the heart rate while an increase in the parasympathetic branch results in a slowing down of the heart rate. Under normal situations there is a balance between these two systems placing the body in a state of homeostasis. However, under a state of mental stress this balance will be altered.[9–11] Heart Rate Variability can be used to detect this change in system balance.[9–11]

Heart rate variability has been extensively applied in understanding the function of the ANS.[9,10,12–15] Figure 2

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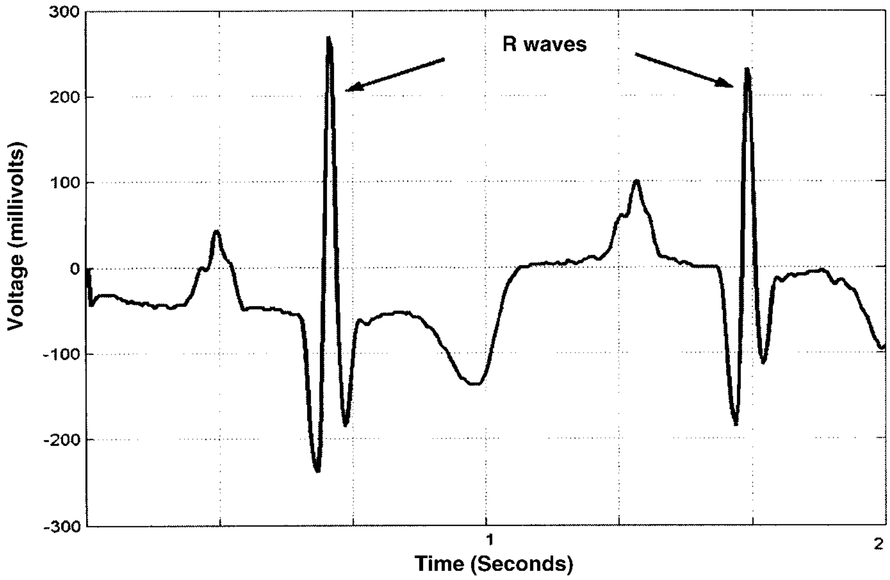

Fig. 2. EKG waveform.

shows a typical EKG waveform. The sequence from P wave to T wave represents one heart cycle. The number of such cycles in a minute is called the *heart rate* and is typically 70–80 cycles (beats) per minute at rest.[16]

The Interbeat interval (IBI), which is beat-to-beat interval, is defined as the time in millisecond between two normal "R" to "R" waves of an Electrocardiogram. The IBI is a valuable index for measuring heart rate variability. The IBI variability can be determined either in the *time domain* or in the *frequency domain*. Time domain analysis has the limitation of needing very large sets of data (~24 hrs) for accurate analysis.[6] Frequency analysis does not have this shortcoming and allows the use of much smaller data sets. Since we are interested in measuring stress during a task, we prefer frequency domain analysis to time domain analysis.

Frequency domain analysis has proven valuable in linking physiological abnormalities and variabilities to specific frequency bands. Parasympathetic and sympathetic nervous system activity has been associated with two frequency bands. The high frequency (HF) component (0.15–0.4 Hz) measures the influence of the vagus nerve in modulating the sinoatrial node and is associated with parasympathetic nervous system activity.[10–13,15] The low frequency (LF) component (0.04–0.15 Hz.) provides an index of parasympathetic effects on the heart.[10,12,14,15] These associations between frequency bands and nervous system activity have been made through the use of functional and pharmacological testing.[13,14]

When a human being is mentally stressed, it is commonly observed that the parasympathetic activity of his/her heart decreases and the sympathetic activity increases. We have exploited this feature of heart rate variability to detect stress in a human subject.

2.2. *Signal Processing*

As mentioned above, the EKG signal is used to calculate the IBI signal. A frequency domain analysis of this IBI signal is useful in detecting physical abnormalities. The particular abnormality, stress that we are looking at in this paper shows its effect in parasympathetic and sympathetic frequency ranges. The signal processing mainly involves observing behavior in these frequency bands, and deducing the physiological state based on its analysis.

Figure 3 shows a flow-chart outlining the steps involved in the analysis of EKG data. When power spectral analysis is done on the IBI calculated from the EKG signal, the range of frequencies corresponding to parasympathetic and sympathetic activity can be identified for a person. This however, does not give us any time domain information regarding the non-stationary nature of the signal.

Short Term Fourier Transformation (STFT) gives a partial solution to the above problem. STFT is a windowed version of the Fourier Transformation. The signal is assumed to be stationary for small intervals over which the Fourier transformation is performed. But STFT has its limitation due to the uncertainty principle, which states that there is a trade off between locality in the frequency domain and locality in time domain. Hence both frequency and time of an event cannot be accurately predicted simultaneously.

Wavelet Transform (WT) is a suitable alternative to STFT as it allows both frequency, and time localization of the signal with reasonable accuracy.[17] This transformation is based on representing a given function as a sum of time shifted (translated) and scaled (dilated) representations of some functions called mother wavelets.[18]

The Continuous Wavelet Transform (CWT) of a function $f(t)$ can be written as:

$$CWT_{\varphi}(a,t) = \frac{1}{\sqrt{|a|}} \int f(t)\, \varphi\left(\frac{t-\tau}{a}\right) dt \tag{1}$$

where $\psi(t)$ is Mother wavelet, a is the Scaling factor, τ is the Time shifting parameter.

A mother wavelet is a function with special properties. Wavelet's most useful feature is the time and frequency localization of the mother wavelet. A single wavelet generates a family of wavelets by dilating and shifting itself

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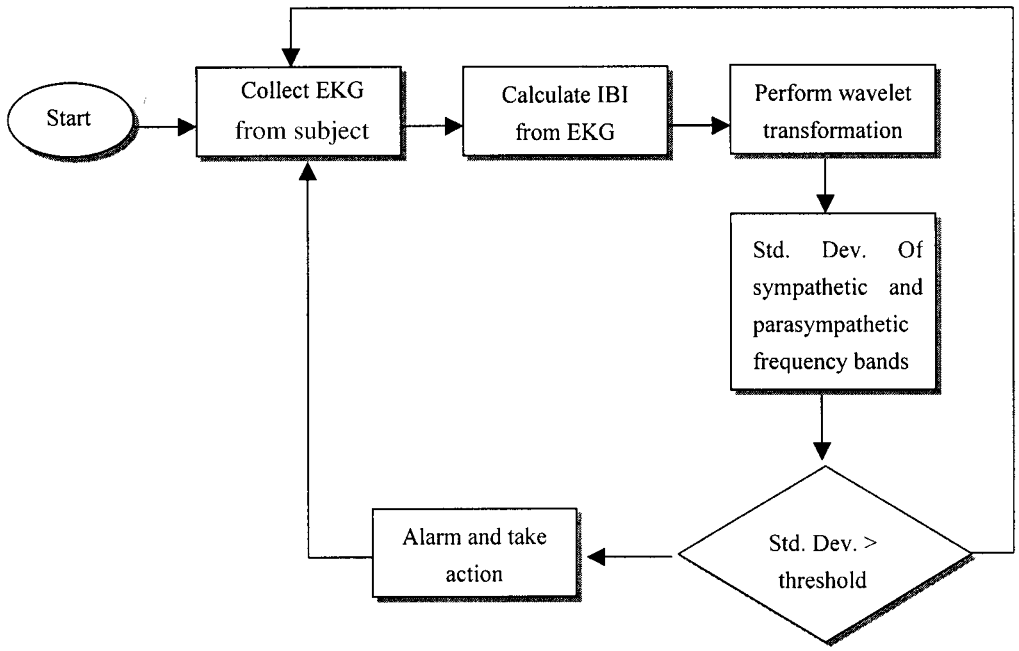

Fig. 3. Flow chart for signal processing.

over a continuum of dilation and translation values.[17,18] By varying the values of a and τ, we can scan the entire signal. For any given value of a and τ, the above transform calculates the coefficient that quantifies the similarity between the function $f(t)$ and the mother wavelet that has been scaled by a and shifted by τ. The CWT gives information regarding the time-frequency characteristics of the function $f(t)$, over the entire time-frequency domain if we choose a mother wavelet such that it has enough time-frequency localization. Calculating wavelet coefficients at every possible scale involves a lot of computation and generates excessive data. Hence we choose to use discrete wavelet transform (DWT), in which scales and positions are based on powers of two.

Several factors should be considered while choosing the mother wavelet for a particular signal processing.[19] An orthogonal basis can be useful in analyzing discrete signals, while non-orthogonal basis for the wavelet can better represent smooth, continuous variations in the signal. The shape of signal is another important factor to be considered. The mother wavelet should be selected or designed such that it reflects the type of feature present in the time series of the signal. In general, it can be said that the wavelet chosen should reflect the type of feature present in the time series. Hence, for a time series signal with sharp jumps, one may choose Harr wavelet, while a smoother function should be chosen for a smooth signal.

In Discrete Wavelet Transform[20,21] the signal $f[n]$ of length N is decomposed into approximation coefficients $s[n]$ and detail coefficients $d[n]$ by the use of two quadrature mirror filters $g[n]$ and $h[n]$, which can be computed from the shifted and dilated versions of the mother wavelet $\psi(t)$ and of a scaling function $\varphi(t)$. A wavelet analysis can be seen as a filtering operation where the high frequency component appears in the detail coefficients and low frequency component in the approximation coefficients. The detail coefficients are not decomposed further. At any given level n, the detailed coefficient vector $d[n]$, will have $N/2^j$ elements (the original signal has N elements) and will cover the frequency range $\Delta f/2^j$. Hence, we observe that at every level of decomposition, the frequency resolution is doubled and the time resolution is halved as the approximation coefficients span one half of the frequency band and the detail coefficients span the other half. Generally, the detail coefficients are not analyzed any further. In this paper, one of the frequency bands of interest exists in the detail coefficient, hence wavelets pose a limit to our analysis. To overcome this limit we extend the analysis to wavelet packet decomposition.

In the Wavelet Packet (WP) decomposition,[22,23] the approximation coefficients as well as the detail coefficients are recursively decomposed using the same filtering and down sampling techniques that are used in DWT. Figure 4 shows the difference between the wavelet decomposition and wavelet packet decomposition. A wavelet packet analysis provides us with a convenient tool to analyze a signal for a desired frequency without losing the time information. The wavelet packets can be used for numerous expansions of a given signal, from which we can capture the exact frequency band that we are interested in.

The WP decomposition of the input signal is performed by computing the convolution of the signal $f[n]$ with the wavelet atoms:

$$w[n] = 2^{-j/2} \sum_k f[n]\, W_p(2^{-j/2}k - n) \qquad (2)$$

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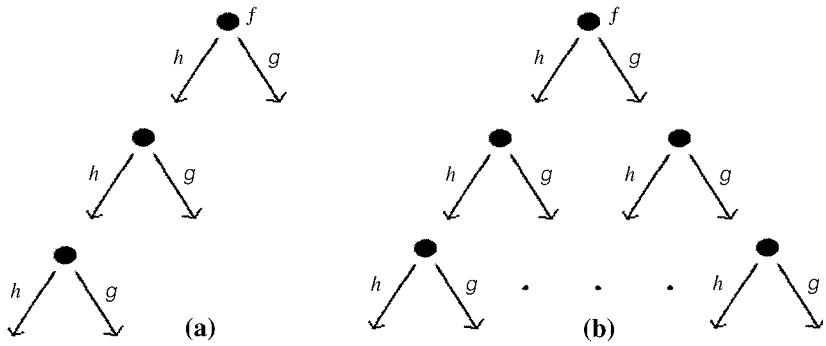

Fig. 4. (a) Wavelet decomposition; and (b) wavelet packet decomposition.

These wavelet atoms can be obtained from the high pass filter ($g[n]$) and the low pass filter ($h[n]$)

$$W_{2p}(t) = \sqrt{2}\sum_{n} h[n]\, W_p(2t - n) \tag{3}$$

$$W_{2p+1}(t) = \sqrt{2}\sum_{n} g[n]\, W_p(2t - n) \tag{4}$$

Each atom W_p $(2^{-j/2}k - n)$ is characterized by three parameters – frequency p, scale j, and position m. For our purpose, we have used the Daubechies wavelet filter db5. This wavelet has been used because it best extracts the frequency contents that are required to analyze the IBI signal. The wavelet db5 has been used for EKG signal processing in many cases.[24] After experimenting with various mother wavelets, we also found db5 to give better results than the other wavelets.

2.3. Decision Making Using Fuzzy Logic

2.3.1. General Overview. For meaningful Human-robot interaction, it is important that the robot interprets the physiological signals of the subject intelligently to deduce his/her stress level.

To obtain the stress level of a given human subject, we monitor his/her heart rate variability, extracting informative features from that signal. Since the transition from a relaxed physiological state to a stressed one is a gradual process, these states cannot be treated as classical sets, which will either wholly include a given feature or exclude it. Hence the decision regarding whether a feature belongs to a stressed or a relaxed state is not a binary one.

In such a case, fuzzy reasoning can prove invaluable in making the decision-making process resemble human reasoning. Fuzzy logic is based on the theory of fuzzy sets. Fuzzy set theory implements classes or groupings of data with boundaries that are not sharply defined (i.e. fuzzy). A fuzzy set can contain elements with only a partial degree of membership. This enables the fuzzy models to exercise flexibility in capturing various aspects of vagueness in the data available to us.[25] Fuzzy set theoretic methods have been used extensively for pattern recognition in the past.[26–28] We can identify the patterns indicating mental stress using features extracted from the heart rate variability of the subject.

As explained in Section 2.2, we know that the sympathetic and the parasympathetic activities of the heart are indicators to the level of mental stress. In the fuzzy model that we use here, the input variables are the standard deviation of the IBI signal in the sympathetic and parasympathetic frequency ranges and the output is the stress index.

The design and implementation of this fuzzy model involves the following steps:[29,30] (1) Specifying the input and output variable membership functions; (2) Fuzzification of the input variables; (3) Defining the rule statements that relate the input variables to the output; (4) Aggregating all outputs (Fuzzy Inference); and (5) Defuzzification of the output variable. The Fuzzy system has been shown in Figure 5.

2.3.2. Definition of membership functions. A Fuzzy set F in a space of points S = {s} is a set of elements with a varying grade of membership and is characterized by a membership function $M_F(s)$ that maps each element of S to a real number in the interval [0 1]. The value of $M_F(S)$ for any given s, indicates the degree of s in F or the degree an s belongs to F.[31] The value 1 indicates complete inclusion of s in F, the value of 0 indicates complete exclusion of s in F, and the intermediate values indicate partial inclusion. There is a wide variety of membership functions built from piecewise linear functions, the Gaussian distribution function, the sigmoid curve, or the quadratic and cubic polynomial curves as these standardized functions have adjustable parameters.

2.3.3. Fuzzification of inputs. Fuzzification of inputs is necessarily determining the degree to which they belong to each of the appropriate fuzzy sets via membership functions.[30] We resolve the inputs into a number of different fuzzy linguistic sets: Sympathetic activity shows relaxation; sympathetic activity shows stress, parasympathetic activity shows relaxation. Before the rules can be evaluated, the inputs must be fuzzified according to each of these linguistic sets. For example, to show to what extent does the sympathetic activity shows stress, we can fuzzify it into the following two sets: relaxation and stress.

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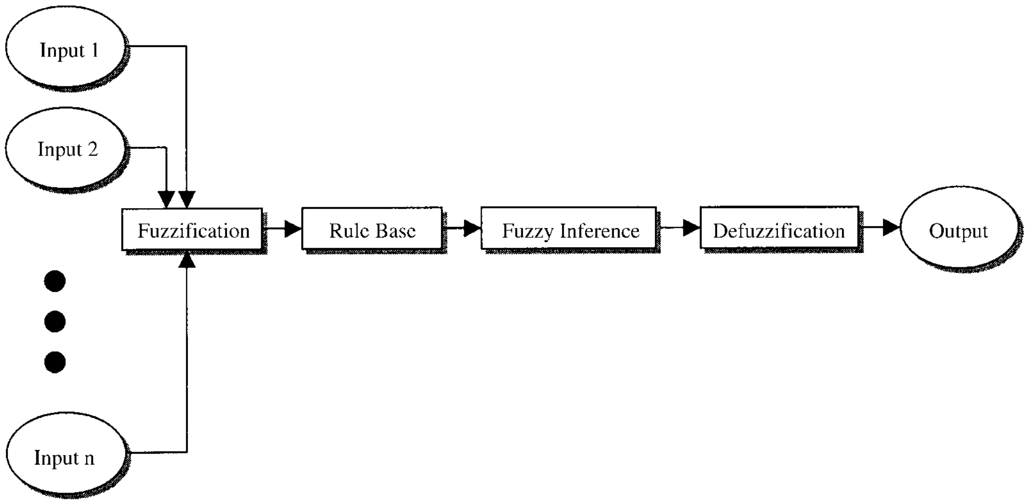

Fig. 5. Fuzzy model.

2.3.4. Definition of rules. The next step is laying down certain rules, which relate the inputs to an output. The parallel nature of the rules is one of the most important aspects of fuzzy logic systems. The transition from a region where the system's behavior is dominated by one rule to a region where another dominates it is smooth, avoiding sharp switching between modes based on breakpoints. A single fuzzy if-then rule assumes the form:

if x *is* A *then* y *is* B

Where A and B are linguistic values defined by fuzzy sets on the ranges (universes of discourse) X and Y, respectively. The if-part of the rule "x *is* A" is called the *antecedent* or premise, while the then-part of the rule "y *is* B" is called the consequent or conclusion. The antecedent of a rule can have multiple parts connected by the logic "AND" or "OR."

if x_1 is A and x_2 is B then y is C

Every rule has a *weight* (a number between 0 and 1), which is applied to the number given by the antecedent. Generally this weight is 1 (as it is for this example) and so it has no effect at all on the implication process. From time to time we may want to weight one rule relative to the others by changing its weight value to something other than 1.

2.3.5. Aggregating Output (Fuzzy Inference). Since decisions are based on the testing of all of the rules, the rules must be combined in some manner in order to make a decision. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set.[30] The output of the aggregation process is one fuzzy set for each output variable.

All the rules are evaluated together and the output of each rule is combined, or aggregated, into a single fuzzy set whose membership function assigns a weighting for every output value.

2.3.6. Defuzzifcation of the output. The defuzzification process transforms the fuzzy set (the aggregate output fuzzy set) into a single number. The aggregate of a fuzzy set encompasses a range of output values, and so must be defuzzified in order to resolve a single output value from the set.

This defuzzification method could employ methods like centroid, bisector, middle of maximum (the average of the maximum value of the output set), largest of maximum, smallest of maximum and other such criteria.

3. EXPERIMENT

There are three major components in the stress detection task. First, we generate reliable mental stress data in laboratory conditions. Second, we process the physiological signals that are collected using wearable biofeedback sensors. Third, we infer the underlying psychological state from the processed physiological signals.

3.1. Stress Generation

One of the most challenging aspects of this research is to gather accurate physiological data related to mental stress in a human being. The aim of the experiment was to generate mental stress in human subjects by simulating an adequate environment of stress in the laboratory. A typical session measuring stress or relaxation lasted for 10 minutes wherein the data was continuously acquired and processed. We have simulated mental stress by making the subject play video games of varying levels of difficulties. Gathering accurate physiological data pertaining to stress is made difficult by several practical problems.

Design and implementation of experiments simulating mental stress in a human subject requires considerable insight into human psychology. Unlike physical stress, mental stress is difficult to simulate and sustain. From a host of activities that trigger mental activity in a subject we need to select those that are most successful in generating stress. Another problem is validating the data pertaining to stress. We also need to consider the day-to-day variability and subject variability. Moreover the data is very sensitive to the manner of sensor placement, sudden body motion and the subject's state of mind during that particular session. This needs to be taken into account too.

We have tried to overcome most of these limitations in our experiments. Activities like playing video games,

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solving puzzles, arithmetic problems, anagrams usually generate mental stress. We chose playing video games as it was found to very effective in bringing the subject under pressure of performance and hence stressing him out. Since the level of difficulties can be varied, we can get data pertaining to varying levels of stress. Although there is no definite way of finding out whether the data gathered is genuine or not, self-reporting from the subject undergoing the experiments has proven to be a reliable method.[8] We have used this self-assessment of the subject regarding his level of stress before we proceed to process the data for feature extraction.

3.2. Physiological Signal Processing

We mounted an EKG sensor on the subjects' body, the positive and negative terminals placed above and below the heart, respectively, and the ground terminal placed on the right side of the chest. The real time monitoring of the EKG signal was done using the wearable EKG sensors and Procomp+data acquisition system.[32] The Procomp+sensors are small and comfortable to wear without interfering with a person's normal activities. The digitally sampled sensor information is sent to the serial port of the computer using a fiber optic cable (Figure 1). The serial interface of Matlab has been used for online data acquisition and processing of the EKG signal. The signal processing includes IBI calculation, wavelet packet analysis and obtaining standard deviation of the IBI frequency spectrum.

The data varies from subject to subject, though the basic characteristics of the frequency spectrum of the IBI signal from most human subjects remains the same. Our experiments across subjects have verified these characteristics. We have gathered data from a single subject over many weeks of time in order to isolate the specific characteristics shown by the frequency spectrum of his IBI signal. Once we identify the frequency ranges that correspond to his sympathetic and parasympathetic activities, we can look for variations in these ranges as his stress level changes. We can employ the same methodology for gathering and analyzing the data from another subject since our approach is generic.

Day-variability is a small change that occurs in one's physiology over time. Comparing data from a typical stress generating session with a reference data gathered on the same day minimizes day variability. The reference data is obtained from a relaxed subject who is not engaged in any mental or physical activity. Quiet breathing, listening to music and leisure reading are some of the activities that put the subject at ease. The data taken during these sessions are pertaining to a stress-free state and can be used for thresholding other data.

The results that are discussed in the following sections were arrived at after several experiments generating stress of varying intensity were conducted on several subjects. These experiment were conducted over a period of 6 months, giving reliable stress indicating data.

3.3. Inference of the psychological state

The raw EKG signal obtained from a subject (Figure 6) is an index of his heart rate variability during the session. The interbeat interval as calculated from this signal is shown in Figure 7.

Since research in the field of heart rate variability shows that mental stress is reflected in the sympathetic and parasympathetic frequency bands, we need to identify these frequency ranges for the subject (Subject A). In order to determine these frequency ranges, we observe the frequency spectrum of the IBI signal obtained from the raw EKG signal.

In order to study subject variability and day-to-day variability, we analyzed data gathered from multiple subjects over a period of several months. This has yielded some valuable conclusions, which have been presented below. Figure 8 and Figure 9 show the power spectral density plot of the IBI signal obtained from two different experiments conducted on separate days on the same subject. Both the experiments were of similar nature as they aimed at generating mental stress in the subject by means of

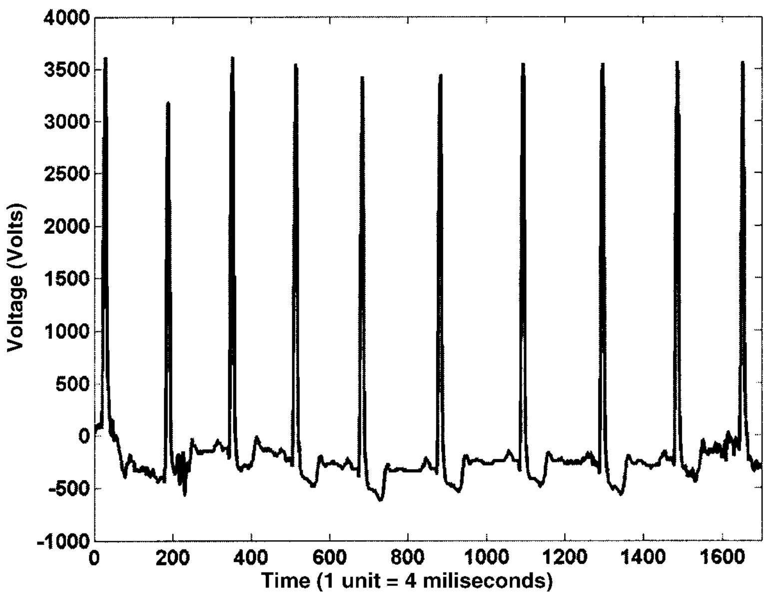

Fig. 6. EHG waveform of Subject.

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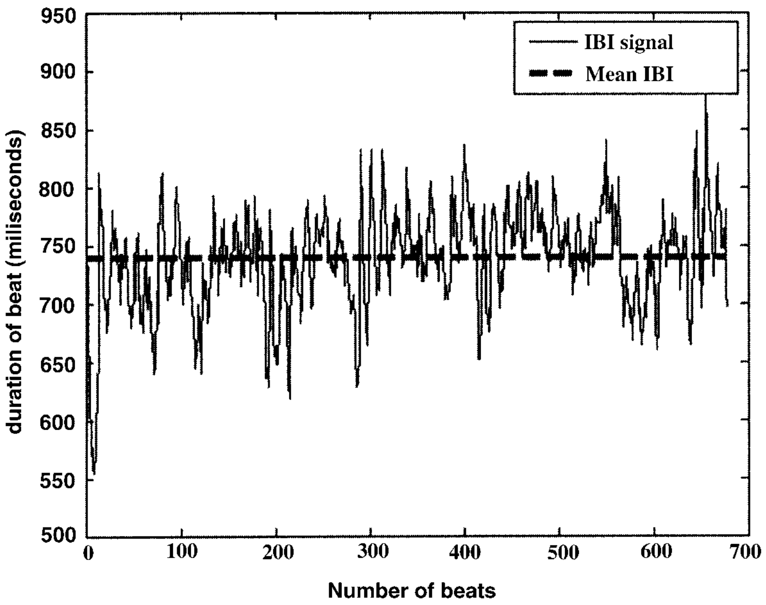

Fig. 7. Interbeat interval as derived from the EKG waveform above.

similar activity in almost identical environments. These figures illustrate the phenomena of day-to-day variability. This variability can be attributed to several factors like the mental and physical health of the subject on that particular day, manner of sensor placement and the accuracy of self-assessment. We observe that the sympathetic and parasympathetic activities occur at the frequency bands, 0.05–0.125 Hz and 0.2–0.3 Hz, respectively. The amplitude of the peaks changes from day to day but the sympathetic and parasympathetic frequency ranges remain almost the same for a particular subject across experiments.

Figure 10 shows the power spectral density plot of the IBI signal obtained from another subject (Subject B) by the same kind of experiment. Comparing this figure with Figure 8 and Figure 9 we detect the occurrence of subject variability. The frequency ranges at which Subject B show sympathetic and parasympathetic activities are not identical to those of Subject A. However, there is an easily observable underlying similarity in all these frequency spectrums of the IBI data gathered on different days from different subjects.

As expected, with an increase in the level of mental stress, the power in the sympathetic band increases and the power in the parasympathetic band decreases. After the frequency bands of interest have been identified by FT, we use Wavelet Packet Decomposition to analyze the heart rate variability of the subject in real time. As explained in the preceding section, Wavelet Packet Decomposition allows sufficient time-frequency localization to detect the variations in the exact frequency band that we are interested in with corresponding timing information.

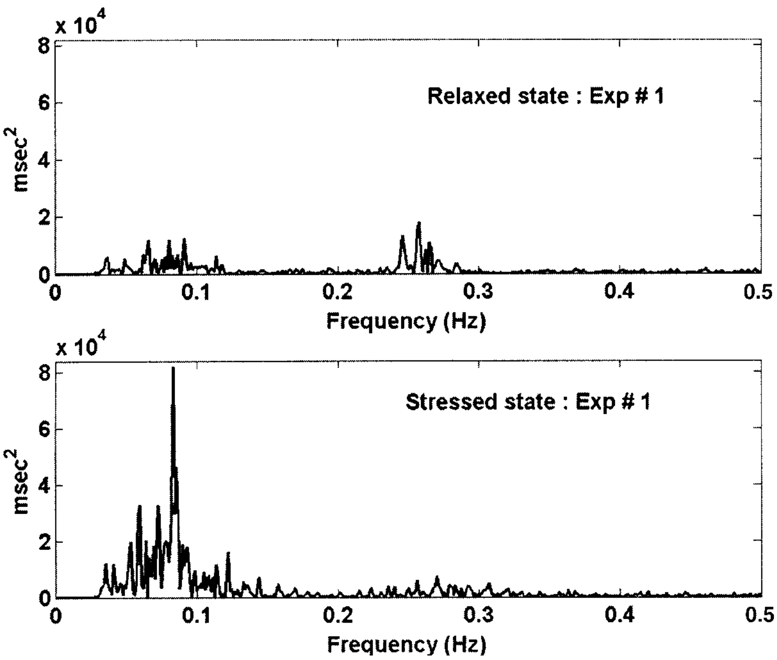

Fig. 8. FT of the IBI signal from Subject A during experiment No. 1.

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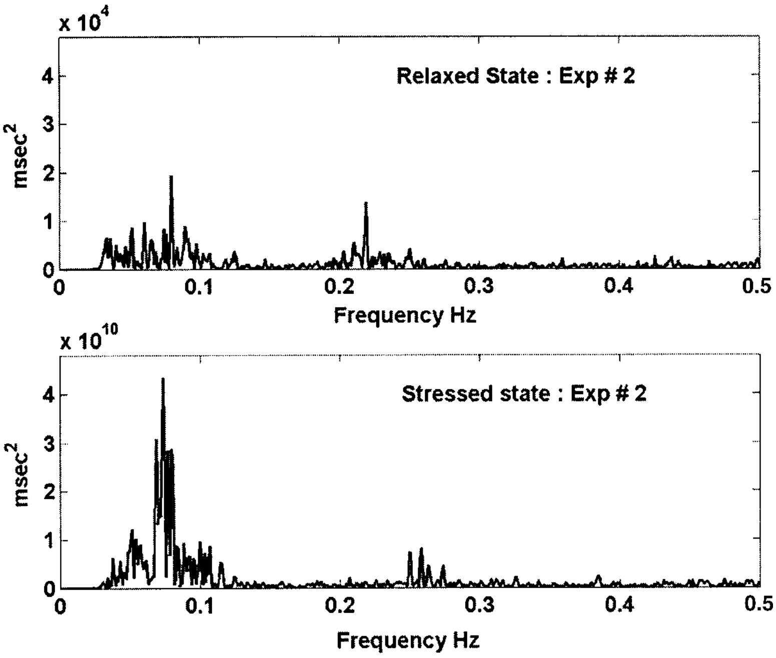

Fig. 9. FT of the IBI signal from Subject A during experiment No. 2.

Figure 11 shows how the Wavelet packet tree decomposes the signal into components. The IBI signal is progressively filtered and down sampled until we capture the exact frequency content of the signal that we are interested in. The frequency bands of interest are the ranges corresponding to sympathetic and parasympathetic activities for the subject. Once we have zoomed down to the exact frequency range, we need to extract a feature from the signal that can be used as an index for detecting mental stress.

Standard deviation of the signal in frequency range of concern proves to be a reliable index for such detection. As expected we find that as the subject gets stressed, the variation in this index is most pronounced in the sympathetic and parasympathetic frequency ranges. For any given IBI signal we calculate the standard deviation in the two above-mentioned frequency ranges. These values are then compared to the standard deviation in the same bands computed from the reference signal.

Figure 12 compares the standard deviation of wavelet packet coefficients at the frequency ranges of interest. A change in standard deviation in the coefficients corresponds to a change in signal power at that frequency range. In

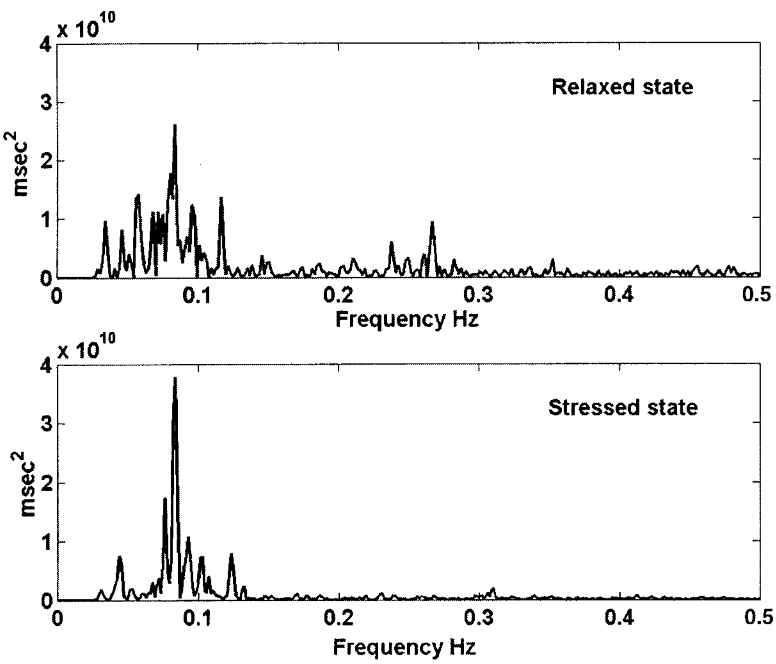

Fig. 10. FT of the IBI signal from Subject B.

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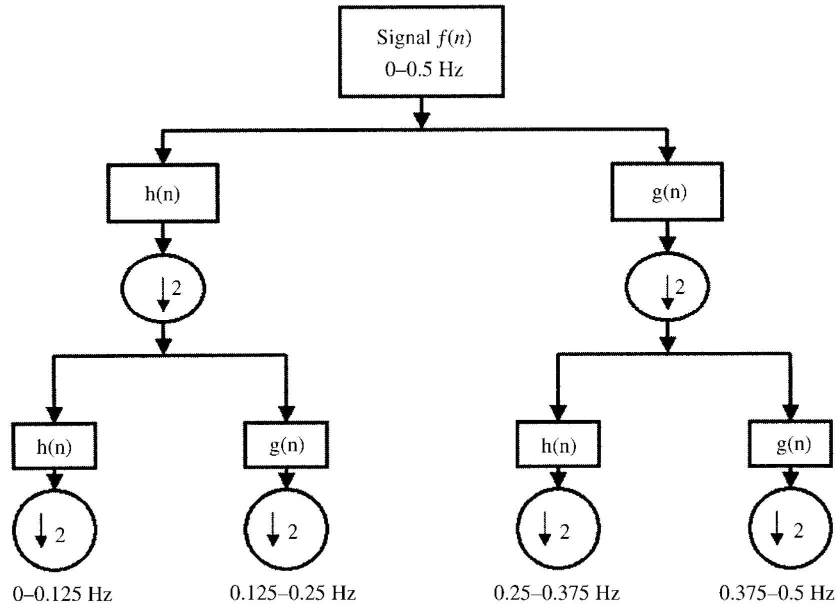

Fig. 11. Wavelet packet decomposition tree showing frequency division.

Figure 12, the first two bars refer to the standard deviations in the frequency range 0.094–0.109 (sympathetic activity range) and the third and fourth bars refer to the frequency range 0.25–0.3125 (parasympathetic activity range). In the various experiments that we conducted, it was consistently observed that as the subject gets stressed, the standard deviation of his sympathetic activity increases and that of his parasympathetic activity decreases as compared to the respective standard deviations when he is relaxed. In Figure 12 the lighter bars indicate the standard deviation of the IBI signal in the sympathetic and parasympathetic frequency ranges calculated from the heart rate variability of the subject when he was completely relaxed. The black bars indicate the same when he was considerably stressed. It can be seen that as theorized in the preceding sections, the sympathetic and the parasympathetic frequency ranges are the ones that register maximum change during a transition from relaxed to stressed mental state. Hence stress detection can be reliably based on the monitoring of this index of heart rate variability.

3.3. *Fuzzy Inference Model*

Now that we have extracted features, we proceed to build a fuzzy logic system for interpreting these inputs to detect whether or not the subject is showing signs of stress. Here we have used Gaussian curve membership functions for the two inputs A_S (sympathetic activity) and A_P (parasympathetic activity) and the output-stress index. The crisp values of the inputs are fuzzified and expressed by the fuzzy sets:

S_P (Index for stress in the parasympathetic range);
R_P (Index for relaxation in the parasympathetic range);
S_S (Index for stress in the sympathetic range);
R_S (Index for relaxation in the sympathetic range).

Similarly the output signal is expressed by the fuzzy sets:

S_L (Least stress);
S_M (Medium stress);
S_H (High stress).

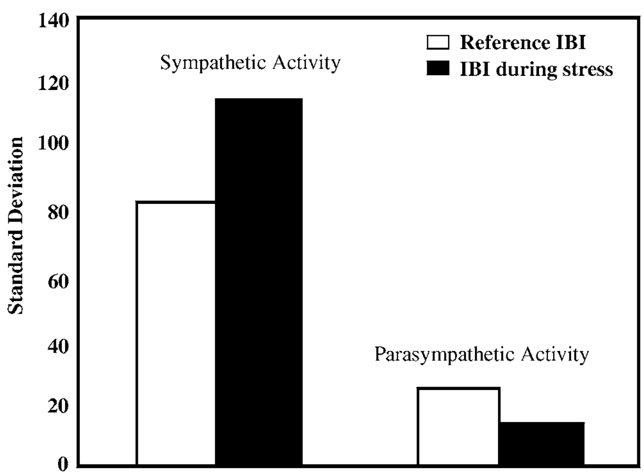

Fig. 12. Standard deviation of the signals in the sympathetic and parasympathetic frequency range when relaxed and stressed.

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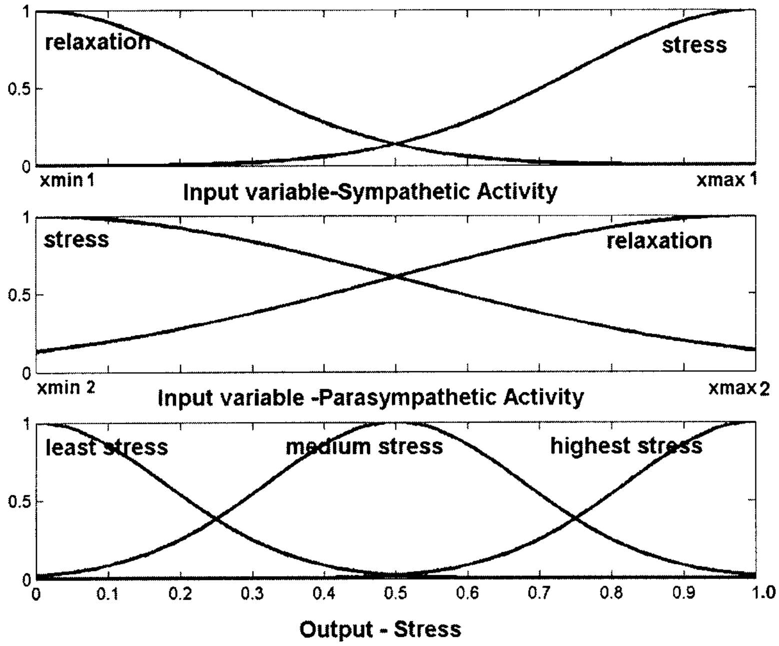

Fig. 13. Membership function plots.

Figure 13 shows the membership function plots for the inputs and the output. The membership functions of the fuzzy sets that define the input are as follows:

$$M_{S/R} = e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

where μ and σ are the mean and standard deviation values for stress and relaxation indices in the sympathetic and parasympathetic activity ranges that determine the shape and position of the membership functions.

Since all the input measurements are compared to the baseline values, we need to adjust the scale first. The input parameters are bounded by $x_{\min}$ and $x_{\max}$, which are determined after performing several experiments on a subject. Here, for the inputsympathetic activity, we have expressed x as the ratio of the standard deviation of the IBI signal in the sympathetic activity range to the standard deviation of the reference signal. $x_{\min}$ is the value of x when the signal shows least stress or when it emulates the reference signal. $x_{\max}$ is the value of x when the signal shows maximum stress. We have chosen the values of x after experimentation (Table I).

The membership functions of the fuzzy sets that define the output are as follows:

$$M_{S/R} = e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

$\mu = 0$ For least stress

$\mu = 0.5$ For medium stress

$\mu = 1.0$ For highest stress

Table I. Values of $x_{\min}$ and $x_{\max}$.

Activity	$x_{\min}$	$x_{\max}$
Sympathetic	1.0	1.55
Parasympathetic	0.53	1.0

We now define the rules that determine the output, given certain input variables.

Rule (i). If the parasympathetic activity index shows relaxation and the sympathetic activity index shows relaxation, the stress in the subject is least.
Rule (ii). If the parasympathetic activity index shows stress and the sympathetic activity index shows relaxation, the stress in the subject is medium.
Rule (iii). If the parasympathetic activity index shows relaxation and the sympathetic activity index shows stress, the stress in the subject is medium.
Rule (iv). If the parasympathetic activity index shows stress and the sympathetic activity index shows stress, the stress in the subject is highest.

The fuzzy inference process is implemented using these rules. The output of each rule is combined to make an aggregate output that is then defuzzified to obtain an output on a scale of [0 1] that indicates the degree of stress in the subject.

We can also view the three-dimensional output surface that shows the variance of the output with the change in the two input variables (Figure 14).

We checked the results of the fuzzy logic system with data from Subject A and Subject B. The subjects were made mentally stressed and their heart rate variability was monitored. From the EKG data, the features corresponding to the sympathetic and parasympathetic activities were extracted. The results have been shown in Table II.

Comparing the values of outputs -0.837 and 0.806 in Table II to the output membership function in Figure 13, we find that they lie close to the highest stress state. This fuzzy logic system can either be trained with data from a single subject to get very accurate results pertaining to his inputs or it can be trained with data from a single subject to get very accurate results pertaining to its inputs or multiple subjects to get reasonably accurate results for each subject.

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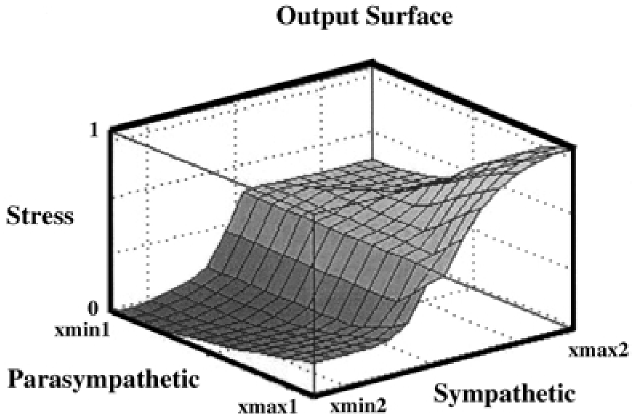

Fig. 14. Three-dimensional output surface.

Table II. Stress Index obtained from the Fuzzy Logic.

Subject	Inputs		Output
	Sympathetic Activity	Parasympathetic Activity	Stress Index
A	1.60	0.52	0.837
B	1.45	0.54	0.806

4. CONCLUSION AND FUTURE WORK

We have presented a novel technique for online stress detection by monitoring the sympathetic and parasympathetic activity of the heart of a human. This method uses wearable computing and is suitable for human-robot cooperative activity. We have used wavelet decomposition and fuzzy logic techniques to determine the stress during an ongoing task. While a robot controller is not developed that can sense stress and respond accordingly, the complete architecture and concepts are presented in the paper.

There are a few limitations to the current work. Gathering accurate physiological data pertaining to specific emotional states, simulating stress environment for eliciting adequate response, day variability and subject variability are few of them.

Future work will focus on overcoming these limitations and integrating this stress detection technique with a robot controller system that takes adequate measures after implicitly detecting stress in a human working in the same environment.

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